Exhibit 1

[REDACTED/PUBLIC VERSION]

IN THE UNITED STATES DISTRICT COURT
FOR THE NORTHERN DISTRICT OF CALIFORNIA
SAN JOSE DIVISION

CONFIDENTIAL – TO BE FILED UNDER SEAL
SUBJECT TO PROTECTIVE ORDER

IN RE: HIGH-TECH EMPLOYEES ANTITRUST LITIGATION **THIS DOCUMENT RELATES TO:** **ALL ACTIONS**	**No. 11-CV-2509-LHK**

EXPERT REPORT OF EDWARD E. LEAMER, PH.D.

October 28, 2013

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I. Introduction, Assignment, and Summary of Conclusions

1. I have been asked by counsel for the Plaintiffs in this case to analyze the impact on members of the Class[1] of the Defendants' conspiracy to restrain competition for each others' employees, which they accomplished through a set of Non-Compete Agreements. I have addressed this question in four prior reports dated October 1, 2012 (the "Leamer Report"); December 10, 2012 (the "Leamer Reply Report"); May 10, 2013 (the "Leamer Amended Report"); and July 12, 2013 (the "Leamer Amended Report"). In those prior reports I explained how and why the agreements impacted the compensation of the Defendants' workforces, including members of the Class. I stand by the opinions and analyses stated in those reports, which I attach to this report as Exhibits A - D and incorporate by reference herein. I reserve the right to testify at trial (if asked) to any and all of the opinions and other matters discussed in my prior reports or in my depositions in this case.

2. In my first report of October 1, 2012, I described a methodology (regression analysis) for showing impact and calculating damages to the Defendants' workforces as a whole and demonstrated how it could work.[2] In this report, I present my revised analysis of Class undercompensation and damages arising from the Non-Compete Agreements. The revision is made necessary by some small changes to the list of titles in the Class, revisions to some of the data series including revenues from Lucasfilm and Pixar, and some minor changes in the model that allow more reliable damage estimates. I also address some questions raised by counsel for the Defendants as possible criticisms of this work, such as

[1] I understand that the Class includes: "All natural persons who work in the technical, creative, and/or research and development fields that are employed on a salaried basis in the United States by one or more of the following: (a) Apple from March 2005 through December 2009; (b) Adobe from May 2005 through December 2009; (c) Google from March 2005 through December 2009; (d) Intel from March 2005 through December 2009; (e) Intuit from June 2007 through December 2009; (f) Lucasfilm from January 2005 through December 2009; or (g) Pixar from January 2005 through December 2009. Excluded from the Class are: retail employees; corporate officers, members of the boards of directors, and senior executives of all Defendants." Order Granting Plaintiffs' Supplemental Motion for Class Certification, October 24, 2013.

[2] Expert Report of Edward E. Leamer, October 1, 2012, pp. 62-70.

supposed peculiarities of Intel's workforce,[3] and show that these features either do not exist or have no meaningful impact on the analysis.

3. The materials I relied upon in the preparation of this report are listed in Exhibit 1 as well as the exhibits to my previous reports (Exhibits A - D). I reserve the right to consider any further relevant evidence that might emerge and to revise my opinions if needed.

II. Background

A. Defendants and the Alleged Agreements

4. In my previous Reports I described my understanding of the alleged Non-Compete Agreements. Based on my review of the evidence in this case and on the Plaintiffs' Supplemental Answers and Objections to Defendants' Second Set of Interrogatories, I understand that the time periods during which Defendants are believed to have participated in Non-Compete Agreements are as follows:[4,5]

[3] Deposition of Edward E. Leamer, June 11, 2013 at pp. 817.

[4] See ADOBE_001096-097 and 231APPLE002145 (Adobe-Apple); PIX00003419 (Apple-Pixar); 231APPLE002140 and 231APPLE073139 (Apple-Google); GOOG-HIGH TECH-00008281-284 (Google-Intel); GOOG-HIGH TECH-00008342-350 (Google-Intuit); and Deposition of James Morris, August 3, 2012 at p. 93 (Lucasfilm-Pixar). Although there is evidence that the Non-Compete Agreement between Pixar and Apple dates from prior to 2005, the start date cannot be given with certainty due to a lack of evidence. I have therefore conservatively assumed, solely for purposes of computing damages, that Apple did not join the conspiracy until 2005.

[5] These dates are based on the earliest notice sent to a party to the alleged agreement. I understand that Apple and Google each received a Civil Investigative Demand ("CID") on March 13, 2009. I have made a conservative assumption, which is that the Defendants immediately ceased their illegal activity upon receipt of a CID.

Figure 1: Periods of Participation in Alleged Collusive Agreements

Defendants	Start Date	End Date
(1)	(2)	(3)
Adobe	May 2005	March 2009
Apple	February 2005	March 2009
Google	February 2005	March 2009
Intel	March 2005	March 2009
Intuit	June 2007	March 2009
Lucasfilm	Mid-1980s	March 2009
Pixar	Mid-1980s	March 2009

5. All of the Non-Compete Agreements covered all employees of the respective companies, regardless of employee geography, job function, product group, or time period. Each of the Agreements prohibited cold-calling, meaning that the parties agreed not to solicit each other's employees in any manner. The agreements applied to all recruiters who were either directly employed by or were headhunters hired by the agreeing firms.[6] Some of the agreements included additional terms, such as:

- Do not hire: The parties agreed not to make employment offers to employees of the other firm without specific approval from the current employer's chief executive.[7]
- Pre-notify: The parties agreed to notify each other prior to making an offer to hire an employee at the other firm.[8]

[6] See e.g., 231APPLE001164, GOOG-HIGH TECH-00023500-601 at 520-528, and PIX00000400.

[7] When present, this provision applied even when an employee initiated contact. Even if certain agreements may not have begun with this express provision, they often operated in this manner in practice. For example, Pixar and Google sought Steve Jobs' permission before making offers to Apple employees. See PIX00006025; 231APPLE002151. Apple refused to consider Adobe employees unless they first left employment with Adobe. See 231APPLE080776 ("This is a response I received from an ADOBE employee who applied for a position through our job posting site. I called him to ensure he is still an ADOBE employee, explained our mutual agreement / guidelines, and asked that he contact me should his employment with ADOBE terminate, but at this time I am unable to continue exploring with him. ... I do not want anything in 'writing'.") Apple also attempted to enter into a "no hire" agreement with Palm, which Palm's CEO, Ed Colligan, rejected. See PALM00005 – 008 at 006 and PALM00022 – 027 at 024. See also, 231APPLE002153 - 154, and 231APPLE002214.

[8] See e.g., PIX00000400; GOOG-HIGH TECH-00056790.

- No counteroffer: The initiating firm that makes an offer to an employee of the other firm agreed not to improve its initial offer if the offer was matched by the other firm.[9] In other words, "no bidding wars."[10]

6. I understand that by the end of March 2009, the Department of Justice ("DOJ") had informed certain defendants of the investigation. On June 3, 2009, the New York Times published an article indicating that the DOJ had begun an investigation into the Defendants' hiring practices and the alleged Non-Compete Agreements in particular.[11] I have assumed that the agreements between the defendants ceased to have an effect on their recruiting and hiring activities in March 2009.

B. Plaintiffs and Class Members

7. The members of the Class each worked for a Defendant at a time when that Defendant was a party to at least one such Agreement (excluding retail employees, corporate officers, members of the boards of directors, and senior executives). I summarize the total employment and compensation of these workers in Figure 2 below.

[9] See PIX00000400; LUCAS00009252.

[10] See PIX00004051 ("We just won't get into bidding wars" for employees); LUCAS00013507 ("We have agreed we want to avoid bidding wars.").

[11] Helft, Miguel, "Unwritten Code Rules Silicon Valley Hiring," The New York Times, June 3, 2009, http://www.nytimes.com/2009/06/04/technology/companies/04trust.html?_r=1.

Figure 2: Class Summary

Defendant	Class Period	Number of Class Members	Class Employee Years	Total Class Compensation (Dollars)
(1)	(2)	(3)	(4)	(5)
Adobe	05/05-12/09	3,746	10,305	$ 1,739,814,770
Apple	03/05-12/09	7,427	20,078	[redacted]
Google	03/05-12/09	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
Intuit	06/07-12/09	3,448	5,948	959,986,055
Lucasfilm[1]	01/05-12/09	521	1,324	162,436,291
Pixar	01/05-12/09	881	2,826	514,665,913
TOTAL		**64,625**	**199,489**	**$ 32,829,041,681**

[1]Missing job title information prior to 2005.

Source: Defendants' employee compensation data; SEC filings.

III. Recapitulation of the Relevant Economic Frameworks

8. The Defendants viewed cold-calling as an important means of competing for workers. Cold-calling of workers is a pro-active approach that reaches out to employees who might not respond to other forms of recruiting.[12] Although many firms use cold calling to recruit workers, firms do not appreciate the disruption when other firms cold-call their employees. One way to minimize the disruptive effect of cold calls from other firms is through anticipatory increases in compensation that reduce or eliminate the attractiveness of any future cold calls that might be received. For example, Facebook's active cold-calling of Google's employees in 2010 was countered by Google with an across-the-board increase in compensation, thus illustrating the broad impact cold-calling can have on compensation firm-wide.[13]

[12] For example, ADOBE_002773-002798 at 785 "Focus on 'passive' talent"'… "top performers tend to be entrenched, 'heads down' may be 'willing to listen' if the right opportunity is presented." Also see 76566DOC000085-098 at 092.

[13] See Leamer Report pp.45-47 for a discussion.

9. Cold-calling is part of the information gathering that reveals the nature of outside opportunities both to workers and to employers. All else being equal, increased information implies increased compensation for Class members, because workers' access to information about better opportunities forces firms to increase compensation both preemptively and reactively. The Defendants suppressed compensation by limiting this flow of information about attractive outside opportunities.

10. I have described in my prior reports economic frameworks relevant to understanding the effect of the alleged non-compete agreements, including: (1) price discovery, (2) internal equity, and (3) profit-sharing.[14]

11. "Price discovery" refers to the process by which a market searches for an equilibrium price when information about supply and demand is imperfect. Members of the Class work in a market characterized by imperfect information and the price discovery framework therefore applies to them. The speed at which price discovery operates depends on the manner in which, and how rapidly, information is disseminated among buyers and sellers. Cold-calling is part of the normal information dissemination process, and non-compete agreements that limit the flow of information about opportunities slow down the price discovery process and thus affect each and every labor contract in a way that works adversely for workers and to the benefit of firms engaged in the Non-Compete Agreements.

12. There can be a normal asymmetry in information that works in favor of employers, since employees may have little or no direct access to the nature of contracts offered and accepted by other similar workers either at their own firm or other firms, and workers may rely mostly on "water-cooler talk" perhaps supplemented by Internet sources. Employers, on the other hand, know exactly the nature of the contracts of every one of their employees, and firms often hire private consulting firms to provide information about outside "market" compensation. Absent cold-calling, many labor contracts are negotiated in unequal bargains between informed employers and uninformed employees.

[14] Leamer Report pp. 29-33 and Leamer Report pp. 42-44.

Cold-calling is an important channel of information about outside opportunities that can help employees become better informed and better paid.

13. As I described previously,[15] the information conveyed by a cold call is reinforced by the information provided by other calls, which makes the effect of, e.g., 1000 cold calls greater than 1000 times the effect of a single cold call. This characteristic of information has been called "super-additive" by Dr. Murphy.[16] It is this feature of information that is the reason I have not attempted to trace out the effect of any single cold call but instead have studied the impact of the illegal anti-cold-calling agreements overall.

14. "Internal equity" refers to the tendency of firms to keep compensation packages of different workers roughly in line to minimize the effect on worker morale of adopting a compensation system that subsets of workers feel is "unfair," which can have an adverse effect on productivity. It is the force of internal equity that can help to spread the impact of the Non-Compete Agreements throughout the Class. As I have explained previously, "equity" does not mean "equal," i.e. Defendants need not pay all employees the same in order to observe internal equity. Rather, internal equity puts boundaries on the degree to which pay of different employees can diverge, and tends to require maintenance of a somewhat rigid compensation structure. My prior statistical work (carried out in all four prior reports) demonstrates that such structures existed within Defendants' compensation systems, and my review of the evidence shows that Defendants intentionally maintained them through ordinary features of their pay systems such as salary bands, systematized bonuses and performance reviews, and so forth.[17]

15. "Profit sharing" refers to the sharing of profits from the critical knowledge assets that reside within the minds of technical workers which may largely determine the overall firm success, and the consequent need for firms to find

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[15] Rebuttal Supplemental Expert Report of Edward E. Leamer, Ph.D., July 12, 2013, at pp. 1, 8.

[16] Deposition of Kevin M. Murphy, Ph.D., July 5, 2013, at p. 463.

[17] My review of the evidence includes evidence cited and relied on in drafting my prior reports and also my review of Dr. Hallock's report, which compiles this evidence.

some way to assure that they do not lose these critical firm-specific knowledge assets via employee departures. One way to minimize losses from departures is to pay the workers well enough that they are not attracted to outside opportunities, which can mean sharing of the profits of the jointly owned firm-specific assets. Another way is to limit the workers' knowledge of or access to outside opportunities with Non-Compete Agreements, thus keeping more of the profits for the firm's principals and top management.

IV. Damages Estimate

16. I previously presented a way to estimate damages to the Class in my October 1, 2012 Report, based on individual employee compensation data. I presented an alternative model in my Reply Report based on firm compensation averages, in order to show that the results of the regression are not "sensitive" to criticisms advanced by defense expert Dr. Murphy. These firm-based models also demonstrated how the payroll records of the defendants can be used to estimate the damages caused by the Non-Compete Agreements. However, the form of regression presented in my October 2012 report remains the preferred approach for the reasons explained below. This Report presents a slightly modified and improved model based on changes to the Class and on updated data that were made available since my October 2012 Report. I also discuss some issues I have investigated that seemed potentially important, but turned out to be immaterial.

A. Determinants of Compensation

17. I have used the standard statistical tool of regression analysis to estimate the impact of the illegal conspiracy on the total compensation of Class members. This approach involves an exploration of the determinants of total compensation at the seven defendant firms between 2001 and 2011, the years for which we have the necessary data.

18. Employee compensation is measured using the Defendants' payroll records. Annual total compensation is the base salary as of December, plus bonuses, the value of stock grants and the estimated value of stock options based on valuations reported by the firms in their SEC filings.

19. As I described in my initial report, my regression compensation model includes variables that capture five kinds of effects.[18] This framework remains intact. The categories of variables and corresponding specific choices are:

a. Conduct Effects: How the Non-Compete Agreements affected compensation;

- Periods when the illegal agreements were in effect;

a. Persistence: How compensation effects linger over time;

- Compensation in the previous two years;

b. Worker Effects: How compensation would vary across workers, absent the agreements;

- Age and gender of the worker;
- Worker tenure;
- Location differences;

c. Industry Effects: How compensation would vary over time, absent the agreements;

- Employment in the information sector in San Jose MSA (Metropolitan Statistical Area);
- Defendant hiring;

d. Employer Effects: How compensation would vary across firms, absent the agreement;

- Firm revenue; and
- Firm hiring.

B. Estimating Undercompensation

20. The compensation model in my first Report explained total compensation of each employee divided by the CPI (to adjust for inflation).[19] This model

[18] Leamer Report, paragraph 142

[19] Leamer Report, Figure 20, page 66. Compensation in that model was analyzed in logarithms to facilitate interpretation of percentage effects from the estimated coefficients.

included a CONDUCT variable which took on a value of one in the years when a defendant had a Non-Compete Agreement, and zero otherwise.[20] In a model without dynamics to allow for persistence in compensation effects, the impact of the illegal agreements would be just the estimated coefficient on the CONDUCT variable,[21] which would measure the percentage by which total compensation was suppressed during the period in which the agreements were in place.

21. The intertemporal dynamics needed to explain compensation variability over time do not allow one to read the damages directly from the estimated equation because some of the CONDUCT effect carries over from year to year, and because the effect depends on other variables, for example, the age of the individual. In this setting, the estimated model needs to be run twice to estimate the damages. First, the model is run with the CONDUCT variable reflecting the existence of the Non-Compete Agreements at the times they occurred. Second, compensation is calculated with the CONDUCT variable turned off to reflect what compensation would have been had there been no Non-Compete Agreements. The difference in compensation between these two runs of the model is the estimated reduction in total compensation due to the agreements.

C. Individual Employee Data is Preferred for Estimating Undercompensation

22. In my previous reports, I have analyzed the payroll records of the Defendants--depending on the issue at-hand--at the individual level, at the title level, and at the firm level.

23. For determining if these firms have "somewhat rigid" salary structures, I have argued that it is best to use title averages because the firm-wide effects are more evident in the title averages than in the individual data and also because the title structures are used by the firms to manage internal equity.

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[20] I set the variable to one-half for years in which a Defendant had a Non-Compete Agreement for only part of the year.

[21] The conduct effect varies by age and hiring rate. The variables have been defined so that the conduct coefficient on non-interacted conduct variable is interpreted as the effect on a 38 year-old at a firm with an average hiring rate.

24. For purposes of estimating damages, a model based on individual-level data is the best choice, because individual data contain all the information in the data set, and because the statistical technique of regression properly applied can extract the relevant information from "noisy" individual data and because averages can be influenced by the changing composition of the workforces that comprise the averages. While individual workers are also changing over time, much of that change can be accounted for statistically with variables such as age and firm tenure.

25. Dr. Murphy raised issues regarding the estimation of the standard errors if the employees share common sources of variability that are not included in the model. Because, as I have previously shown, compensation levels of different individuals are correlated, e.g., within job titles, not every single individual can be viewed as an independent "experiment" for purposes of estimating standard errors.

26. On this point, it is important to reiterate, as expressed in my Reply Report, that none of my opinions is reliant on the standard errors.[22] My task is to determine the best possible estimate of the damages. A damage estimate with a large standard error will still be the best estimate, unless there is a more accurate alternative. While a large standard error means that the damages could be smaller, that same large standard error also means the damages could equally well be larger by the same amount. Absent a better estimate, we need to rely on the best we have. Dr. Murphy's technical treatment of this problem, known as "clustered standard errors," changes the standard errors but has no impact on the estimates of damages. Thus, the issue is irrelevant for the task of determining the best estimate once the model is decided upon.

27. I also explained in my Reply Report that the preferred treatment of this correlation problem is to include variables that capture the common sources of variation. This I have done by including firm revenues and San Jose Metro Area "information" employment in my model. But, as my previous work shows, common variation also results independent of these factors, as a consequence of

[22] Leamer Reply Report, paragraph 77

Defendants' maintenance of internal equity. Thus, Dr. Murphy's point about the standard errors has validity, but not relevance, since his adjustment to the standard errors has no impact on the damage estimates. In contrast to the "clustered standard errors" that Dr. Murphy has proposed, the inclusion of a revenue variable does affect the estimate of damages, and thus, is a material inclusion.

28. To confirm the point that Dr. Murphy's criticism has no impact on the damage estimates, I report below my analyses with and without the corrected standard errors per the preference of Dr. Murphy. The estimated coefficients will be exactly the same (and thus the damages computed will be exactly the same with or without the uncorrected standard errors).

29. An alternative approach to the problem of estimating standard errors of the damages is to build the damage estimates from annual averages of compensation for each defendant, instead of the individual data.[23] This is not a complete correction of the standard error problem since there may remain unexplained correlation among the firm average annual compensation levels, but averaging across employees within a firm is likely to eliminate most of the problem since it aggregates the correlated employees into a single observation. The use of annual averages, however, focuses attention on the intertemporal variability in the data set and away from individual heterogeneity measured by employee age, tenure, education, for example. An advantage of individual level data is that it allows for the possibility that changes in the composition of the Class may affect the total damages, a possibility that I suspect to be the case based on the analysis I have done previously of undercompensation with the individual data as well as the economic frameworks and evidence regarding focus of cold calling on somewhat more experienced workers.

30. Furthermore, using firm averages may help with the standard error issue, but it can create a new problem – the firm averages can change over time in part because the mix of employees is changing as some employees depart and some arrive. Thus, some of the variability in firm average compensation is not a

[23] I reported an estimated model based on these annual averages in my Reply Report.

symptom of a change in the compensation schedules but instead is a symptom of the changing mix of employees who comprise the average.

31. Thus, my approach will be to use the individual data with controls that are appropriate for firm success and external market forces. I will report this estimated model both with and without clustered standard errors, with the proviso that these do not affect my opinion.

V. Modifications to the Class Compensation Analysis

32. There have been several changes since my October 2012 Report that affect my analysis. First, I have been asked to analyze undercompensation of the Class only. Second, since my October 2012 Report I received additional data regarding Lucasfilm and Pixar revenues.[24] Third, I have been asked by counsel to exclude certain titles from the Class.[25] Fourth, I have updated the conduct variable in my analysis to be consistent with the June 2007 start date in Figure 1 above. I estimate my compensation model below with these updates.

VI. Modifications Considered and Rejected

33. I have considered and rejected the need for any modifications based on two additional issues (raised by counsel for Intel during my depositions): Intel's substantial employment of persons outside California and Intel's supposed status as principally a maker of hardware, rather than software. Neither of these issues has any bearing on the calculation of damages in this case or, for that matter, the likelihood of impact on all members of the Class.

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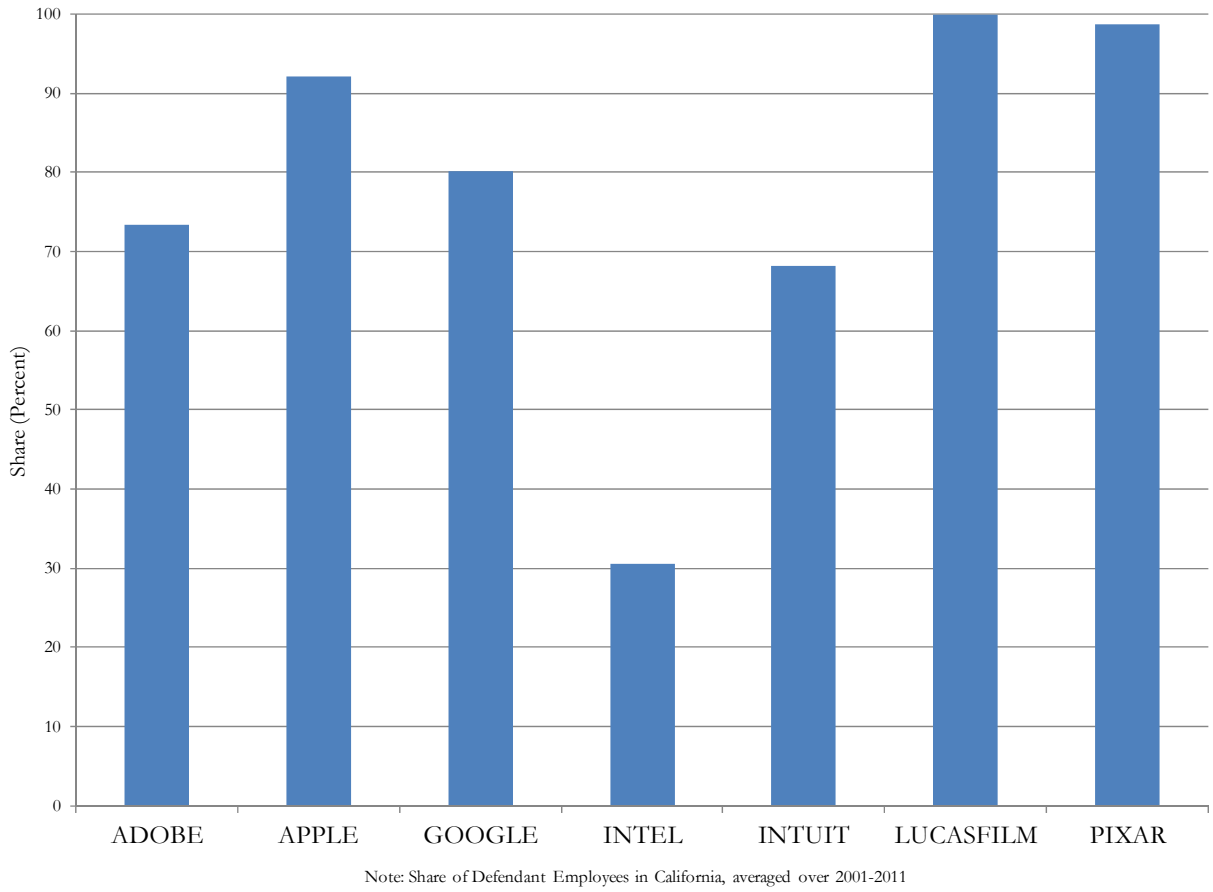
[24] At the time of my original Report several years of Lucasfilm and Pixar revenue data were unavailable to me. Pixar data were later provided with Dr. Murphy's Rebuttal Report and Lucasfilm data were produced by the defendant. This new data increases the number of observations that are usable in the analysis for these two Defendants, thus I have incorporated this data.

[25] Based on instructions from counsel I understand that a number of the job titles I included in the Technical Class in my original analyses are to be excluded from the class (e.g., because they involved Defendants' senior management). I have revised my data to flag those titles for exclusion from the analysis of the Technical Class.

A. Class Members in California Are Not Substantially Different From Those in the Rest of the U.S.

34. Figure 3 shows the fraction of the Class Members who were in California from 2001 to 2011. Intel stands out, having about 30 percent of these workers in California. The other employers have between 70 percent and 100 percent of their technical workforce in California.

Figure 3: Share of Defendants' Technical Employees in California (2001 – 2011)



Note: Share of Defendant Employees in California, averaged over 2001-2011

35. It has been posited that the California workforce compensation is importantly different from the rest of the U.S. My model has state-indicator variables and thus allows for compensation differences based on employee location, but the model does not distinguish the effect of the Non-Compete Agreements in California from the effect in the rest of the U.S. This concern is largely dispelled by the figure below which compares Intel compensation in California and in the rest of the U.S., and the concern is put to rest by a statistical analysis

reported below that allows the CONDUCT effect to be different in California than the rest of the nation.

36. Figure 4 depicts Intel's average Class total real compensation for employees in California compared to those in other parts of the country. [redacted] As I describe below, I confirm the conclusion that this issue has no substantial effect on the estimation of damages by estimating a variation of my model that allows for differences in the impact of the Non-Compete Agreements depending on whether or not the employee was located in California.

B. Intel Produces Software and Competes in the Same Labor Market as Other Defendants

37. Intel sells computer hardware (microprocessors), not software like many of the other defendants, but, as I have commented previously, Intel has software engineers working to produce the code that drives their microprocessors.[26] Indeed, it is a commonly known fact that chip manufacturing is highly automated and relies on software engineers. Or, as Forbes put it, "Intel: The Biggest Software Company You've Never Heard Of."[27] Also, in a recent article titled "Intel the Software Company - Aggressive Campaign to Poach Seattle's Software Engineers," the authors' subheading is "It doesn't take many people to make chips these days because of highly automated fabs but Intel needs a lot of software engineers."[28]

38. In any event, I present below in Exhibit 5 a variation of my compensation model using a hardware employment variable for Intel in addition to the San Jose Information Technology Employment variable. The regression results, and consequently the estimated damages, are not substantially affected.

VII. Estimation of Undercompensation and Calculation of Damages

A. Undercompensation Estimation

39. The analysis I conduct here and the regression damages model is substantially the same as the regression I conducted in my original report with the exception of the changes I described above. The variables I use are summarized in Figure 5. The regression allows the impact of the challenged conduct to vary by firm,

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[26] In my deposition on June 11, 2013, an attorney inquired about the suitability of the industry variable – the employment in the information sector in San Jose – for a study of Intel which is a manufacturer of microprocessors.

[27] Caulfield, Brian, "Intel: The Biggest Software Company You've Never Heard Of," Forbes, May 9, 2012, http://www.forbes.com/sites/briancaulfield/2012/05/09/intel-is-the-biggest-software-company-youve-never-heard-of/

[28] Foremski, Tom, "Intel The Software Company – Aggressive Campaign To Poach Seattle's Software Engineers," Silicon Valley Watcher, June 17, 2013, http://www.siliconvalleywatcher.com/mt/archives/2013/06/intel_the_software_co.php

by year, and by the individual employee's age (as a proxy for their career experience).

Figure 5: Data Definitions

	Variable	Description
	(1)	(2)
1.	Total Annual Compensation	Sum of annual base salary (as of December) plus bonuses, overtime amount, and equity compensation received in the year.
2.	CPI	U.S. Consumer Price Index (St. Louis Federal Reserve).
3.	Conduct	Indicator equal one in years where the Defendant had a Non-Compete Agreement, 1/2 in partial years at the start of the Agreements, 1/4 in 2009 and zero otherwise.
4.	Age	Age of employee in years.
5.	Number of New Hires in the Firm	Number of Class employees newly hired in the year.
6.	Company Tenure	Number of months an employee has been affiliated with the Defendant.
7.	Male	Indicator for male employees.
8.	Location	U.S. State that an employees works in (as of December).
9.	Information Sector Employment San Jose	Employment in San Jose/Santa Clara Valley in the information sector (St. Louis Federal Reserve).
10.	National Hardware Engineer Employment	U.S. Employment in Computer Hardware Engineer Occupation Category (Bureau of Labor Statistics).
11.	Total Number of Transfers among Defendants	Total number of Class employees who moved from one Defendant to another in the year.
12.	Total Number of New Hires	Total number of Class employees hired by all Defendants in the year.
13.	Firm Revenue Per Employee	Global revenue of the company divided by global employment in the company (SEC Filings and Defendant
14.	Firm Profit Per Employee	Global net income of the company divided by global employment in the company (SEC Filings).
15.	Firm Stock Price	Annual Average Adjusted Closing Price of Company Stock (Yahoo Finance).

40. The detailed regression estimates are reported in Exhibit 2. In accordance with the discussion above, I also report a version of the regression estimated using clustered standard errors. (See Exhibit 3.) As I indicated in the discussion above, the coefficient estimates are precisely the same.

41. To explore the robustness of these results to the addition of other variables, I have estimated a version of the model including Defendants' profits per

employee in the previous year and also the level and rate of change of stock prices, all adjusted by the CPI. The profits in the previous year refer to a cash flow of the firm that could be shared with the workforce via increases in compensation. High and/or rising stock prices, controlling for profits, reflect healthy expected future cash flows which may encourage firms to reward their workforce and may make it more attractive to use equity grants and options as a form of compensation. Pixar and Lucasfilm were not publicly traded, so they are excluded from this analysis. I estimate a modified version of my model with these variables below. (See Exhibit 4.) When I calculate undercompensation with this model for the five Defendants that can be included, I find that this model actually finds slightly greater undercompensation than the model that included all seven Defendants but not the stock price and profit variables. Because this model with these additional variables is unable to incorporate all Defendants, I maintain the earlier model as the more conservative, complete estimate.

42. As noted above, although Intel is less of a hardware engineering firm than generally perceived, I also estimated a variation of my model that has been modified to utilize a U.S. computer hardware employment variable for Intel in addition to the Information Sector variable (which I continue to utilize for the other Defendants). (See Exhibit 5.) [redacted] In addition, the overall fit of the model is hardly budged by this amendment. Thus, there is no support in these data for the hypothesis that Intel is hiring mostly hardware engineers, and I therefore use my updated original model for a damage calculation.

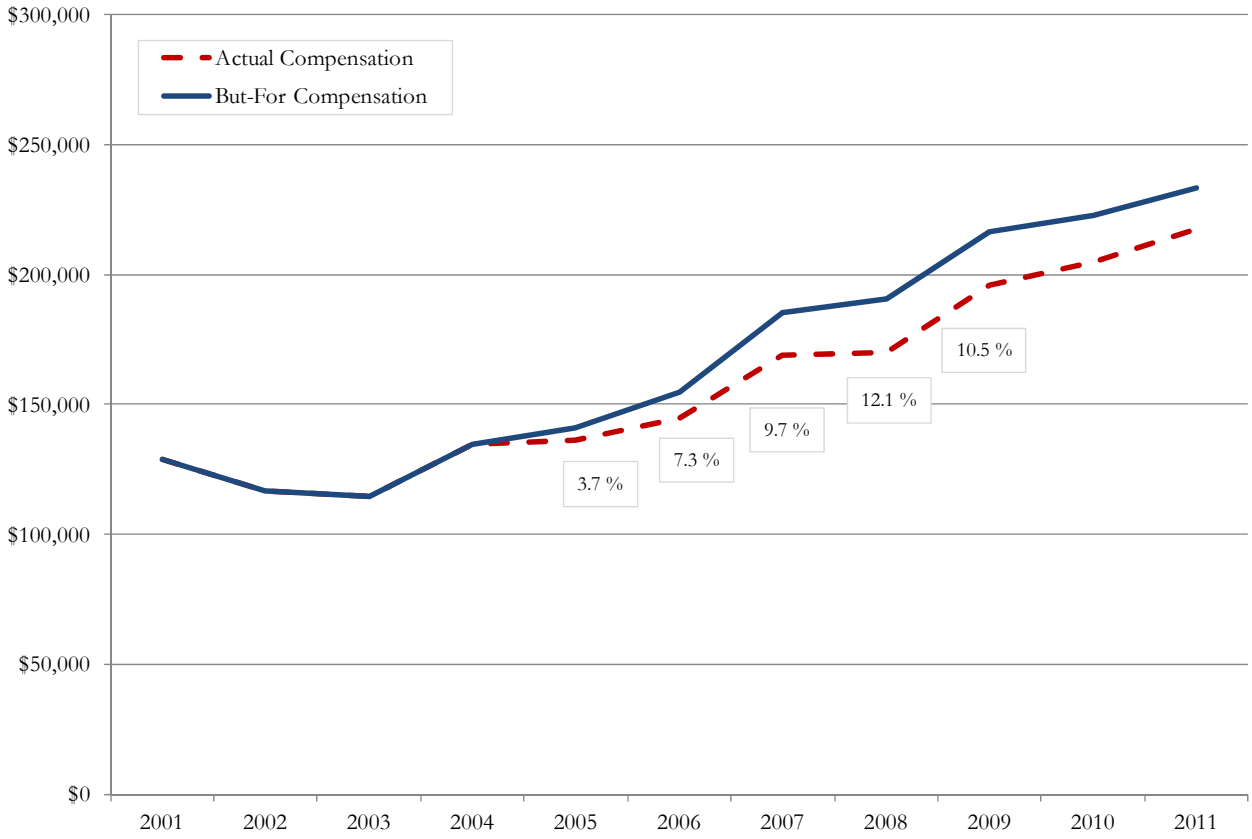
43. As I also described above, most Defendants had two-thirds or more of their employees in California, but Intel had seventy percent of employees outside California. [redacted] The models that I have estimated at the individual level have all included state indicator variables, which allow for fixed differences between California and the rest of the country, for example, a cost of living adjustment. A new model

reported in Exhibit 6 also allows for the possibility that the impact of the anti-cold-calling agreements was different inside of California. The addition of the interaction between CONDUCT and a California indicator does not substantially affect model performance or the estimated conduct effects relative to my compensation model reported in Exhibit 2 (and Exhibit 3).

44. Using the estimation results from Exhibit 2, I compute compensation from the model, but "turning off" the CONDUCT variable. This has the effect of calculating the compensation that Class employees would have received but-for the Non-Compete Agreements. The regression allows the undercompensation to Defendants' workforces to vary by firm and by year, just as in my prior analysis.

45. Figure 6 compares the actual average total compensation of all employees of the seven defendants, with the estimated compensation but-for the Non-Compete Agreements. As may be noted in the figure, the undercompensation effects continue beyond the end of the conduct (indeed, beyond the Class Period). This is the result of the high persistence which my model allows for and estimates. Thus, although the conduct is assumed to have ended in March 2009, the damages are calculated to the end of the Class Period in December 2009.

Figure 6: The Impact of the Non-Compete Agreements: Actual Average Total Compensation vs. But-For Compensation



Note: Undercompensation Percentages depicted for Class Period Compensation

46. The estimates of total but-for compensation by year are reported in the third column of Figure 7. Comparing this compensation during the Class Period to the actual compensation received in column two, I estimate the Class was undercompensated by $3.06 billion (9.3 percent of the $32.8 billion in the total compensation of Class during the Class Period).

Figure 7: Damages

Year	Total Class Compensation	But-For Compensation	Total Damages	Under-Compensation
	(Dollars)			(Percent)
(1)	(2)	(3)	(4)	(4)/(2) (5)
2005	$ 3,754,796,647	$ 3,892,532,340	$ 137,735,693	3.7 %
2006	5,832,175,462	6,255,377,845	423,202,383	7.3
2007	7,032,235,802	7,715,647,752	683,411,951	9.7
2008	7,403,583,390	8,296,458,370	892,874,980	12.1
2009	8,806,250,380	9,734,209,682	927,959,300	10.5
TOTAL	**$ 32,829,041,681**	**$ 35,894,225,990**	**$ 3,065,184,307**	**9.3 %**

Source: Defendants' employee compensation data; Conduct Regression Results.

Edward E. Leamer, Ph.D.
October 28, 2013

Exhibit 1
List of Materials Relied Upon

Pleadings and Orders		**Date**
Order Granting Plaintiffs' Supplemental Motion for Class Certification		10/24/13

Depositions and Exhibits		**Date**
Leamer, Edward	Vol. 2	06/11/13
Murphy, Kevin	Vol. 2	07/05/13

Expert Reports

Expert Report of Edward E. Leamer	10/01/12
Reply Expert Report of Edward E. Leamer	12/10/12
Supplemental Expert Report of Edward E. Leamer	05/10/13
Rebuttal Supplemental Expert Report of Edward E. Leamer	07/12/13
Expert Witness Report of Kevin Hallock	05/10/13

Publicly Available Materials

Bureau of Labor Statistics, "Occupational Employment Statistics - Computer Hardware Engineers"

Caulfield, Brian, "Intel: The Biggest Software Company You've Never Heard Of," Forbes, May 9, 2012, http://www.forbes.com/sites/briancaulfield/2012/05/09/intel-is-the-biggest-software-company-youve-never-heard-of/

Foremski, Tom, "Intel The Software Company – Aggressive Campaign To Poach Seattle's Software Engineers," Silicon Valley Watcher, June 17, 2013, http://www.siliconvalleywatcher.com/mt/archives/2013/06/intel_the_software_co.php

Exhibit 2: Compensation Model

Observation: Employee ID record in December of each year
Dependant Variable: Log(Total Annual Compensation/CPI)

Variable	Estimate (1)	St. Error (2)	T-Value (3) (1)/(2)
1. Conduct * (Log Age - Log(38))	1.1774 ***	0.1045	11.2686
2. Conduct * (Log(Age)^2 - Log(38)^2)	-0.1590 ***	0.0142	-11.1894
3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92)	-0.0170 ***	0.0012	-14.7160
4. Conduct	-0.0559 ***	0.0017	-32.7948
5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6766 ***	0.0074	91.3587
6. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7288 ***	0.0037	196.7834
7. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4329 ***	0.0022	194.3166
8. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6819 ***	0.0030	224.5316
9. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6524 ***	0.0090	72.7760
10. LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.9332 ***	0.0526	17.7540
11. PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6740 ***	0.0087	77.4714
12. ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3037 ***	0.0073	41.8148
13. APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2457 ***	0.0039	63.4696
14. GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3687 ***	0.0022	168.9056
15. INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2840 ***	0.0029	96.5466
16. INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.3048 ***	0.0087	35.0852
17. LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.0428	0.0524	0.8157
18. PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.0941 ***	0.0080	11.7713
19. Log(Age) (Years)	-0.6561 ***	0.0616	-10.6445
20. Log(Age)^2	0.0790 ***	0.0084	9.4305
21. Log(Company Tenure) (Months)	0.0177 ***	0.0070	2.5208
22. Log(Company Tenure)^2	-0.0012	0.0008	-1.5611
23. Male	0.0056 ***	0.0009	6.5675
24. DLog(Information Sector Employment in San-Jose)	1.8770 ***	0.0250	74.9374
25. Log(Total Number of Transfers Among Defendants)	0.1032 ***	0.0017	60.2020
26. Year (trend)	-0.0042 ***	0.0004	-9.9182
27. Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0263 ***	0.0014	18.8437
28. Log(Total Number of New Hires)	-0.3350 ***	0.0035	-96.0550
29. Log(Firm Revenue Per Employee/CPI) (-1)	-0.0475 ***	0.0043	-10.9572
30. DLog(Firm Revenue Per Employee/CPI) (-1)	0.1364 ***	0.0038	36.2599
31. APPLE	0.1252 ***	0.0254	4.9381
32. GOOGLE	1.3597 ***	0.0268	50.7544
33. INTEL	0.1032 ***	0.0227	4.5481
34. INTUIT	0.1290 ***	0.0349	3.6980
35. LUCASFILM	0.0563	0.0867	0.6488
36. PIXAR	1.3792 ***	0.0495	27.8446
37. Location (State) Indicators	YES		
38. Constant	YES		
R-Square	**0.868**		
Observations	**277,119**		

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.
(2) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.
(3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
(4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of employees, both obtained from SEC Filings. Lucasfilm and Pixar revenues obtained from defendant documents.
(5) Observations are restricted to cases in which there was no change in employer in the previous two years.

Source: Defendants' employee compensation data; St. Louis Fed Reserve; SEC Filings

Exhibit 3: Compensation Model with Clustered Standard Errors

Observation: Employee ID record in December of each year
Dependant Variable: Log(Total Annual Compensation/CPI)

Variable	Estimate (1)		Robust St. Error (2)	T-Value (3) (1)/(2)
1. Conduct * (Log Age - Log(38))	1.1774	***	0.4419	2.6647
2. Conduct * (Log(Age)^2 - Log(38)^2)	-0.1590	***	0.0582	-2.7324
3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92)	-0.0170		0.0304	-0.5584
4. Conduct	-0.0559		0.0447	-1.2519
5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6766	***	0.0582	11.6193
6. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7288	***	0.0579	12.5888
7. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4329	***	0.0720	6.0097
8. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6819	***	0.0320	21.2969
9. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6524	***	0.0492	13.2621
10. LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.9332	***	0.0804	11.6141
11. PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6740	***	0.1467	4.5959
12. ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3037	***	0.0472	6.4374
13. APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2457	***	0.0405	6.0608
14. GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3687	***	0.0514	7.1772
15. INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2840	***	0.0278	10.2182
16. INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.3048	***	0.0447	6.8157
17. LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.0428		0.0820	0.5217
18. PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.0941		0.1167	0.8065
19. Log(Age) (Years)	-0.6561	***	0.1979	-3.3161
20. Log(Age)^2	0.0790	***	0.0253	3.1268
21. Log(Company Tenure) (Months)	0.0177		0.0452	0.3927
22. Log(Company Tenure)^2	-0.0012		0.0047	-0.2589
23. Male	0.0056	**	0.0025	2.2123
24. DLog(Information Sector Employment in San-Jose)	1.8770	***	0.4704	3.9905
25. Log(Total Number of Transfers Among Defendants)	0.1032	***	0.0381	2.7105
26. Year (trend)	-0.0042		0.0083	-0.5044
27. Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0263		0.0267	0.9860
28. Log(Total Number of New Hires)	-0.3350	***	0.0691	-4.8491
29. Log(Firm Revenue Per Employee/CPI) (-1)	-0.0475		0.0714	-0.6648
30. DLog(Firm Revenue Per Employee/CPI) (-1)	0.1364	*	0.0752	1.8144
31. APPLE	0.1252		0.2600	0.4817
32. GOOGLE	1.3597	***	0.4378	3.1055
33. INTEL	0.1032		0.2721	0.3793
34. INTUIT	0.1290		0.2201	0.5861
35. LUCASFILM	0.0563		0.2919	0.1928
36. PIXAR	1.3792	***	0.3909	3.5283
37. Location (State) Indicators	YES			
38. Constant	YES			
R-Square	**0.868**			
Observations	**277,119**			

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.
(2) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.
(3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
(4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of employees, both obtained from SEC Filings. Lucasfilm and Pixar revenues obtained from defendant documents.
(5) Observations are restricted to cases in which there was no change in employer in the previous two years.
(6) Standard Errors adjusted for clustering at employer-year level.

Source: Defendants' employee compensation data; St. Louis Fed Reserve; SEC Filings

Exhibit 4: Compensation Model with Added Variables

Observation: Employee ID record in December of each year
Dependant Variable: Log(Total Annual Compensation/CPI)

Variable	Estimate (1)		Robust St. Error (2)	T-Value (3) (1)/(2)
1. Conduct * (Log Age - Log(38))	0.9885	***	0.4211	2.3472
2. Conduct * (Log(Age)^2 - Log(38)^2)	-0.1343	***	0.0549	-2.4469
3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92)	-0.0572		0.0404	-1.4158
4. Conduct	-0.1149	**	0.0551	-2.0866
5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6763	***	0.0678	9.9718
6. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7356	***	0.0612	12.0285
7. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4424	***	0.0751	5.8921
8. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6783	***	0.0365	18.6017
9. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6230	***	0.0615	10.1358
10. ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3037	***	0.0579	5.2446
11. APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2450	***	0.0414	5.9226
12. GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3705	***	0.0432	8.5747
13. INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2891	***	0.0325	8.8986
14. INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.3296	***	0.0563	5.8571
15. Log(Age) (Years)	-0.6435	***	0.1952	-3.2964
16. Log(Age)^2	0.0772	***	0.0248	3.1180
17. Log(Company Tenure) (Months)	0.0041		0.0407	0.1000
18. Log(Company Tenure)^2	0.0002		0.0042	0.0445
19. Male	0.0051	**	0.0025	2.0564
20. DLog(Information Sector Employment in San-Jose)	1.9455	***	0.4492	4.3313
21. Log(Total Number of Transfers Among Defendants)	0.1172	***	0.0411	2.8494
22. Year (trend)	-0.0052		0.0103	-0.5021
23. Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0700	*	0.0389	1.8004
24. Log(Total Number of New Hires)	-0.3723	***	0.0559	-6.6589
25. Log(Firm Revenue Per Employee/CPI) (-1)	0.1245		0.1632	0.7631
26. DLog(Firm Revenue Per Employee/CPI) (-1)	0.2047	*	0.1051	1.9472
27. (Profit Per Employee/CPI) (-1)	-0.2509		0.1555	-1.6138
28. Log(Annual Average Stock Price/CPI)	0.0529		0.0456	1.1613
29. DLog(Annual Average Stock Price/CPI)	-0.0961		0.0895	-1.0738
30. APPLE	-0.0565		0.3264	-0.1731
31. GOOGLE	1.1636	**	0.5397	2.1562
32. INTEL	0.1069		0.2784	0.3841
33. INTUIT	0.1338		0.2157	0.6202
34. Location (State) Indicators	YES			
35. Constant	YES			
R-Square	**0.875**			
Observations	**271,773**			

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.
(2) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.
(3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
(4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of employees, both obtained from SEC Filings.
(5) Firm Profit Per Employee is computed as a ratio of global net income to global number of employees, both obtained from SEC Filings.
(6) Firm Stock Prices obtained From Yahoo Finance
(7) Observations are restricted to cases in which there was no change in employer in the previous two years.
(8) Lucasfilm and Pixar omitted due to lack of data.
(9) Standard Errors adjusted for clustering at employer-year level.

Source: Defendants' employee compensation data; St. Louis Fed Reserve; SEC Filings

Exhibit 5: Compensation Model with Hardware Employment Variable

Observation: Employee ID record in December of each year
Dependant Variable: Log(Total Annual Compensation/CPI)

Variable	Estimate (1)		Robust St. Error (2)	T-Value (3) (1)/(2)
1. Conduct * (Log Age - Log(38))	1.2249	***	0.4451	2.7520
2. Conduct * (Log(Age)^2 - Log(38)^2)	-0.1649	***	0.0582	-2.8313
3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92)	0.0180		0.0397	0.4541
4. Conduct	-0.0529		0.0451	-1.1735
5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.7354	***	0.0589	12.4873
6. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7544	***	0.0624	12.0845
7. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4415	***	0.0775	5.6951
8. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6847	***	0.0343	19.9417
9. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.7093	***	0.0492	14.4194
10. LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.9201	***	0.0796	11.5541
11. PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.7039	***	0.1421	4.9532
12. ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.2447	***	0.0622	3.9341
13. APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2374	***	0.0416	5.7098
14. GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3639	***	0.0463	7.8669
15. INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2820	***	0.0268	10.5030
16. INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2533	***	0.0431	5.8749
17. LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.0504		0.0807	0.6244
18. PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.0929		0.1132	0.8207
19. Log(Age) (Years)	-0.7033	***	0.2080	-3.3803
20. Log(Age)^2	0.0850	***	0.0264	3.2156
21. Log(Company Tenure) (Months)	-0.0040		0.0453	-0.0890
22. Log(Company Tenure)^2	0.0009		0.0047	0.1911
23. Male	0.0058	**	0.0025	2.2863
24. DLog(Information Sector Employment in San-Jose) * (1-INTEL)	1.0474	**	0.5002	2.0940
25. DLog(Information Sector Employment in San-Jose) * INTEL	2.2309		0.6474	3.4458
26. DLog(National Hardware Engineer Employment) * INTEL	-0.3697	***	0.0974	-3.7945
27. Log(Total Number of Transfers Among Defendants)	0.0747	**	0.0326	2.2878
28. Year (trend)	-0.0120		0.0080	-1.4995
29. Log(Number of New Hires In the Firm/Number of Employees(-1))	-0.0597		0.0586	-1.0190
30. Log(Total Number of New Hires)	-0.1839	***	0.0588	-3.1276
31. Log(Firm Revenue Per Employee/CPI) (-1)	0.0197		0.0781	0.2524
32. DLog(Firm Revenue Per Employee/CPI) (-1)	0.0953		0.0583	1.6352
33. APPLE	0.0078		0.2860	0.0272
34. GOOGLE	1.3600	***	0.4708	2.8888
35. INTEL	-0.0026		0.2839	-0.0091
36. INTUIT	0.1303		0.2171	0.6003
37. LUCASFILM	0.0484		0.2867	0.1689
38. PIXAR	1.2292	***	0.3908	3.1456
39. Location (State) Indicators	YES			
40. Constant	YES			
R-Square	**0.870**			
Observations	**277,119**			

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.
(2) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.
(3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
(4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of employees, both obtained from SEC Filings. Lucasfilm and Pixar revenues obtained from defendant documents.
(5) Observations are restricted to cases in which there was no change in employer in the previous two years.
(6) National Employment Statistics for Computer Hardware Engineer Occupation Category from BLS.
(7) Standard Errors adjusted for clustering at employer-year level.

Source: Defendants' employee compensation data; St. Louis Fed Reserve; SEC Filings

Exhibit 6: Compensation Model with Geographic Control Variable

Observation: Employee ID record in December of each year
Dependant Variable: Log(Total Annual Compensation/CPI)

Variable	Estimate (1)		Robust St. Error (2)	T-Value (3) (1)/(2)
1. Conduct * (Log Age - Log(38))	1.1757	***	0.4444	2.6456
2. Conduct * (Log(Age)^2 - Log(38)^2)	-0.1588	***	0.0585	-2.7132
3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92)	-0.0161		0.0311	-0.5169
4. Conduct	-0.0538		0.0467	-1.1504
5. Conduct * (Location State = California)	-0.0032		0.0098	-0.3263
6. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6767	***	0.0583	11.6098
7. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7289	***	0.0578	12.6031
8. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4330	***	0.0721	6.0071
9. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6820	***	0.0321	21.2603
10. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6520	***	0.0492	13.2580
11. LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.9341	***	0.0808	11.5675
12. PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6741	***	0.1467	4.5938
13. ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3035	***	0.0472	6.4372
14. APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2456	***	0.0404	6.0717
15. GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3685	***	0.0513	7.1810
16. INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2840	***	0.0278	10.2175
17. INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.3051	***	0.0448	6.8140
18. LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.0416		0.0823	0.5056
19. PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.0941		0.1168	0.8063
20. Log(Age) (Years)	-0.6553	***	0.1976	-3.3157
21. Log(Age)^2	0.0789	***	0.0252	3.1251
22. Log(Company Tenure) (Months)	0.0176		0.0452	0.3898
23. Log(Company Tenure)^2	-0.0012		0.0047	-0.2558
24. Male	0.0056	**	0.0025	2.2096
25. DLog(Information Sector Employment in San-Jose)	1.8823	***	0.4724	3.9846
26. Log(Total Number of Transfers Among Defendants)	0.1032	***	0.0380	2.7195
27. Year (trend)	-0.0042		0.0083	-0.5056
28. Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0259		0.0266	0.9737
29. Log(Total Number of New Hires)	-0.3354	***	0.0691	-4.8515
30. Log(Firm Revenue Per Employee/CPI) (-1)	-0.0477		0.0716	-0.6660
31. DLog(Firm Revenue Per Employee/CPI) (-1)	0.1365	*	0.0752	1.8155
32. APPLE	0.1256		0.2605	0.4823
33. GOOGLE	1.3599	***	0.4377	3.1071
34. INTEL	0.1031		0.2722	0.3788
35. INTUIT	0.1303		0.2204	0.5913
36. LUCASFILM	0.0580		0.2923	0.1985
37. PIXAR	1.3786	***	0.3913	3.5228
38. Location (State) Indicators	YES			
39. Constant	YES			
R-Square	**0.869**			
Observations	**277,119**			

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.
(2) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.
(3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
(4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of employees, both obtained from SEC Filings. Lucasfilm and Pixar revenues obtained from defendant documents.
(5) Observations are restricted to cases in which there was no change in employer in the previous two years.
(6) Standard Errors adjusted for clustering at employer-year level.

Source: Defendants' employee compensation data; St. Louis Fed Reserve; SEC Filings

EXHIBIT A

to Edward Leamer's 10/28/13 Merits Report

[REDACTED/PUBLIC VERSION]

IN THE UNITED STATES DISTRICT COURT
FOR THE NORTHERN DISTRICT OF CALIFORNIA
SAN JOSE DIVISION

CONFIDENTIAL – TO BE FILED UNDER SEAL
SUBJECT TO PROTECTIVE ORDER

IN RE: HIGH-TECH EMPLOYEES ANTITRUST LITIGATION **THIS DOCUMENT RELATES TO:** **ALL ACTIONS**	**No. 11-CV-2509-LHK**

EXPERT REPORT OF EDWARD E. LEAMER, PH.D.

October 1, 2012

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I. Experience and Qualifications

1. I am the Chauncey J. Medberry Professor of Management, Professor of Economics and Professor of Statistics at the University of California at Los Angeles. I earned a B.A. degree in Mathematics from Princeton University in 1966, and a Masters in Mathematics and a Ph.D. degree in Economics at the University of Michigan in 1970. I was an Assistant and Associate Professor of Economics at Harvard University from 1970 to 1975, and joined the Economics Department at UCLA in 1975 as a Full Professor. I served as Chair of the Department of Economics from 1983 to 1987 and Area Head of Business Economics from 1990 to 1993. I had a tenured appointment in the Economics Department at Yale University in 1995 and I have been a Visiting Professor at several universities, including the University of Chicago. I have been a Guest Professor at the University of Basel in Switzerland, at the Central European University in Prague, Czech Republic, at the Institute for Advanced Studies in Vienna, Austria, and at the Universidad de San Andreas in Buenos Aires, Argentina. I have served as the Director of the UCLA Anderson Forecast since 2000 and Chief Economist of the Ceridian-UCLA Pulse of Commerce Index from 2010-2012.

2. I have published extensively in the fields of econometric methodology and statistical analysis, in international economics, and in macro-economic forecasting. I have written five books and over 90 academic articles, many of which deal with the subject of inferences that may appropriately be drawn from non-experimental data. My academic research in econometrics and international economics has been profiled in **New Horizons in Economic Thought, Appraisals of Leading Economists**, edited by Warren Samuels. My papers in econometrics have been republished in a volume in the Edward Elgar Series: **Economists of the 20th Century**. My research has been funded by the National Science Foundation, the Ford Foundation, the Sloan Foundation, and the Russell Sage Foundation.

3. I am an elected Fellow of two of the most important honorific societies in my field: the American Academy of Arts and Sciences and the Econometric Society. I have been a consultant for the Federal Reserve Board of Governors, the

Department of Labor, the Department of Energy, the International Monetary Fund, the World Bank, the Inter-American Development Bank, and the Treasury of New Zealand. I have been a visiting scholar with the Federal Reserve Board and the International Monetary Fund. I have served as an expert in a variety of matters dealing with issues of interpretation of data.

4. My curriculum vita is incorporated in this report as **Exhibit 1**. My testimonial experience is incorporated in this report as **Exhibit 2.** My hourly rate for time spent working on this matter is $650.

5. I have in this report relied on the best information available to me at the time of its preparation. A list of documents on which I relied in the preparation of this report is provided in **Exhibit 3**. I understand that discovery in this matter is ongoing and that Defendants or third parties may produce additional information that has a bearing on my analysis. I reserve the right to supplement or amend my conclusions as necessary in light of such additional information.

II. Introduction, Assignment, and Summary of Conclusions

6. The defendants in this matter are a group of well-known high-tech firms, namely Adobe, Apple, Google, Intel, Intuit, Lucasfilm, and Pixar ("Defendants").[1]

7. The Plaintiffs' Amended Complaint[2] alleges that the Defendants agreed to limit or eliminate competition for workers amongst each other by refraining from

[1] Adobe Systems Inc. ("Adobe") is a Delaware corporation with its principal place of business located at 345 Park Avenue, San Jose, California 95110, Apple Inc. ("Apple") is a California corporation with its principal place of business located at 1 Infinite Loop, Cupertino, California 95014, Google Inc. ("Google") is a Delaware corporation with its principal place of business located at 1600 Amphitheatre Parkway, Mountain View, California 94043, Intel Corp. ("Intel") is a Delaware corporation with its principal place of business located at 2200 Mission College Boulevard, Santa Clara, California 95054, Intuit Inc. ("Intuit") is a Delaware corporation with its principal place of business located at 2632 Marine Way, Mountain View, California 94043, Lucasfilm Ltd. ("Lucasfilm") is a California corporation with its principal place of business located at 1110 Gorgas Ave., in San Francisco, California 94129, and Pixar is a California corporation with its principal place of business located at 1200 Park Avenue, Emeryville, California 94608.

[2] Re: High-Tech Employee Antitrust Litigation, Consolidated Amended Complaint, September 2, 2011 (Consolidated Amended Complaint).

contacting each others' employees to explore job offers ("Cold-Calling"[3]), limiting their actions in negotiating with their workers, and other restrictions. This was accomplished by means of a collection of express bilateral agreements among the Defendants. I will refer to these agreements, individually and collectively, as the "Non-Compete Agreements," or as the "Agreements."

8. I understand that the Plaintiffs are seeking certification of the following class of employees (the "All-Salaried Employee Class," or, the "All-Employee Class"):

> All natural persons employed on a salaried basis ("salaried employees") in the United States by one or more of the following: (a) Apple from May 2005 through December 2009; (b) Adobe from May 2005 through December 2009; (c) Google from March 2005 through December 2009; (d) Intel from March 2005 through December 2009; (e) Intuit from June 2007 through December 2009; (f) Lucasfilm from January 2005 through December 2009; or (g) Pixar from January 2005 through December 2009. Excluded from the All-Employee Class are: retail employees; corporate officers, members of the boards of directors, and senior executives of all Defendants.

9. I also understand that the Plaintiffs are seeking certification, in the alternative, of the following alternate class of employees (the "Technical, Creative, and Research & Development Class," or, the "Technical Employee Class"):

> All natural persons employed on a salaried basis who work in the creative, research & development, and/or technical fields,[4] in the United States by one or more of the following: (a) Apple from May 2005 through December 2009; (b) Adobe from May 2005 through December 2009; (c) Google from March 2005 through December 2009; (d) Intel from March 2005 through December 2009; (e) Intuit

[3] "Cold-Calling" refers to communicating directly in any manner (including orally, in writing, telephonically, or electronically) with another firm's employee who has not otherwise applied for a job opening.

[4] See Appendix B for a description of how I determined the members of the Technical and Creative Alternate Class.

from June 2007 through December 2009; (f) Lucasfilm from January 2005 through December 2009; or (g) Pixar from January 2005 through December 2009. Excluded from the Technical Employee Class are: retail employees; corporate officers, members of the boards of directors, and senior executives of all Defendants.

10. I have been asked to analyze the following questions with regard to the All-Employee Class and Technical Employee Class defined above:

(a) Is there proof common to each proposed class capable of showing that the Non-Compete Agreements artificially reduced the competition of its members? In order to answer this question, I have been asked to evaluate whether evidence common to each class is capable of showing that the Non-Competition Agreements artificially reduced the compensation of: (i) members of each class generally; and (ii) all or most members of each class?

(b) Is there a reliable Class-wide or formulaic method capable of quantifying the amount of suppressed compensation suffered by each class?

11. Based upon my work to date, I have reached the following conclusions:

(a) There is evidence common to the All-Employee Class and Technical Employee Class, respectively, capable of showing that the Non-Compete Agreements systematically reduced the compensation of the members of each class. Specifically, and as explained in the body of this report, I have concluded that evidence and economic analyses applicable to each class as a whole are capable of showing that compensation to the All-Employee Class and Technical Employee Class was artificially suppressed generally due to the Non-Compete Agreements.

(b) Classwide evidence capable of showing artificial generalized compensation suppression due to the agreements falls into three categories: (1) **labor economic studies and theory** explaining that by reducing or eliminating Cold-Calling and other active competition over employees, the Agreements were likely to have depressed compensation because they impair information flow about compensation and job offers, reduce negotiating leverage of employees, and minimize movement of employees between firms; (2) **documents from Defendants' files** showing the link between "Cold-Calling" and increased compensation; and (3) **multiple regression analyses**, utilizing Defendants' internal compensation and other data, showing that the Agreements artificially suppressed compensation at each Defendant.

(c) I have further found that evidence and economic analysis applicable to each class as a whole are capable of showing that all or nearly all members of the All-Employee Class and Technical Employee Class had their compensation suppressed due to the Agreements. Such classwide evidence falls into three categories: (1) economic studies and theory, especially regarding the interest of firms in preserving "internal equity," demonstrating that the adverse effects on compensation due to a poaching ban would be felt not just by those who would have been poached, but by employees more generally due to the needs of firms to maintain a salary structure; (2) documentary evidence from Defendants' files showing Defendants' own concerns about preserving internal equity, as well as other documentary evidence; and (3) statistical evidence, including a multiple regression analysis, showing that All-Employee Class and Technical Employee Class member compensation at any point in time is governed largely by common factors. What this analysis means is that any generalized suppression of compensation due to the Agreements

would be experienced by all or nearly all members of the All-Employee Class and Technical Employee Class.

(d) Finally, I have concluded that standard economic methods are capable of reliably quantifying the aggregate amount of reduced compensation caused by the Agreements to the All-Employee Class and Technical Employee Class, respectively.

12. The analyses described in this report are performed for the purpose of demonstrating the availability of proof and statistical methodologies common to members of the All-Employee Class and the Technical Employee Class capable of showing that members of each class suffered suppressed compensation due to the Agreements, and capable of quantifying that harm. I understand that discovery has not yet been completed and that further evidence might emerge that is relevant to my analysis. I reserve the right to consider any such evidence and its impact, if any, on the analysis I have proposed.

III. Case and Background

A. Defendants

13. Adobe, founded in 1982, is a technology company with its headquarters in San Jose, California.[5] Adobe is well known for a number of software products including Acrobat, Photoshop, and Illustrator. It is also known for its Flash media platform which it acquired in late 2005 as part of its acquisition of Macromedia, which had been the publisher of Dreamweaver and the Flash media platform.[6] In its 2009 fiscal year, Adobe had nearly $3 billion in revenues.[7]

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[5] Adobe, "Corporate Overview," http://www.adobe.com/aboutadobe/pressroom/pdfs/profile.pdf.

[6] Adobe, "Adobe completes acquisition of Macromedia," http://www.adobe.com/aboutadobe/invrelations/adobeandmacromedia_faq.html.

[7] Adobe Systems Incorporated, "2009 Form 10-K," January 22, 2010 at pp.52.

14. Apple, founded in 1976, is a technology company that is headquartered in Cupertino, California.[8] The company is a market leader in several consumer electronics market segments with its iPad, iPhone, and iPod product lines.[9] Apple has been a leader in the digital music distribution market with its iTunes service.[10] Apple's 2011 total revenues exceeded $108 billion.[11]

15. Google, founded in 1998, is a technology company headquartered in Mountain View, California.[12] The company is the leading internet search provider.[13] The company went public in 2004. Google's revenues reached nearly $38 billion in 2011.[14]

16. Intel is a technology company, headquartered in Santa Clara, California. The company was founded in 1968 and is the world's largest semiconductor chip maker.[15] Intel is most well known for its x86 series of microprocessors, found in most personal computers today[16] but the company also markets other integrated

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[8] Time, "Top 10 Apple Moments," http://www.time.com/time/specials/packages/article/0,28804,1873486_1873491_1873530,00.html.

[9] Reuters,"Company Profile for Apple Inc," http://in.reuters.com/finance/stocks/companyProfile?symbol=AAPL.O.

[10] Whitney, Lance," iTunes reps 1 in every 4 songs sold in U.S," CNET News, August 18, 2009, http://news.cnet.com/8301-13579_3-10311907-37.html.

[11] Apple Inc., "2011 Form 10-K," October 26, 2011 at pp.24.

[12] Google, "Our history in depth," http://www.google.com/about/company/history/.

[13] Google, "Google Launches World's Largest Search Engine," June 26, 2000, McGee, Matt, "Google Still No. 1 Search Engine On Earth," Searchengineland, August 31, 2009 and Google Inc., "2010 Annual Report," February 11, 2011 at p.25.

[14] Google, "2012 Financial Tables – Investor Relations – Google," http://investor.google.com/financial/tables.html.

[15] Intel, "Intel Company Information," http://www.intel.com/content/www/us/en/company-overview/company-facts.html.

[16] Edwards, Benj, "Birth of a Standard: The Intel 8086 Microprocessor," PCWorld, June 16, 2008, http://www.pcworld.com/article/146957-3/birth_of_a_standard_the_intel_8086_microprocessor.html.

circuits and devices related to communications and computing.[17] Intel had revenue of $54 billion in 2011.[18]

17. Intuit is a technology company, headquartered in Mountain View, California.[19] The company was founded in 1983 and is known for its QuickBooks, Quicken and TurboTax software products. In 2011 the company revenues exceeded $3.8 billion.

18. Lucasfilm is a film production company known for its computer animation expertise, headquartered in San Francisco, California. Founded in 1971, the company is best known for producing the Star Wars films, as well as other box office hits, including the Indiana Jones franchise. Lucasfilm has seven different divisions: Industrial Light & Magic, LucasArts, Lucasfilm Animation, Skywalker Sound, Lucas Licensing, Lucas Online and Lucasfilm Singapore. Lucasfilm Animation has studios both in Marin County, California and Singapore.

19. Pixar is a computer animation film studio headquartered in Emeryville, California.[20] The company was founded in 1979 as Graphics Group and later renamed to Pixar in 1986.[21] In 2006 the company was acquired by Disney for approximately $7.4 billion.[22] Prior to the acquisition, in 2005 Pixar had annual revenues of nearly $290 million.[23]

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[17] Intel, "Intel Products," http://www.intel.com/p/en_US/products/productsbyintel.

[18] Intel Corporation, "2011 Annual Report," February 23, 2012 at p.2.

[19] Intuit, "Intuit: Corporate Profile," http://about.intuit.com/about_intuit/profile/.

[20] Pixar, "Pixar: Welcome," http://www.pixar.com/about.

[21] Pixar, "Pixar History: 1986," http://www.pixar.com/about/Our-Story.

[22] Pixar, "Pixar History: 2006," http://www.pixar.com/about/Our-Story and "Disney buying Pixar for $7.4 billion,"NBC News, 1/25/2006, http://www.msnbc.msn.com/id/11003466/ns/business-us_business/t/disney-buying-pixar-billion.

[23] Pixar, "2005 10-K," March 7, 2006 at p.37.

B. The Non-Compete Agreements

20. I have studied the allegations of the Plaintiffs' complaint and evidence of the Non-Compete Agreements. I have not been asked to form an opinion on the ultimate question of whether or not the Defendants reached anticompetitive agreements or should be liable under the law. However, I have reviewed evidence about the agreements and their enforcement to understand their scope and duration for purposes of my analysis, and to assure myself that certain assumptions I have made fit the circumstances.

21. Based on that review, I understand the time periods of the alleged Non-Compete Agreements to have been as follows.

Figure 1: Periods of the Alleged Collusive Agreements

Defendants	Start Date[24]	End Date[25]
(1)	(2)	(3)
Adobe-Apple	May 2005	March 2009
Apple-Pixar	April 2007	March 2009
Apple-Google	February 2005	March 2009
Google-Intel	March 2005	March 2009
Google-Intuit	June 2007	March 2009
Lucasfilm-Pixar	Before 2000	March 2009

22. I also understand that Defendants entered into several additional agreements. Those agreements include: (1) an agreement between Pixar and Intel that began in approximately October 2008,[26] and (2) agreements Apple apparently had with

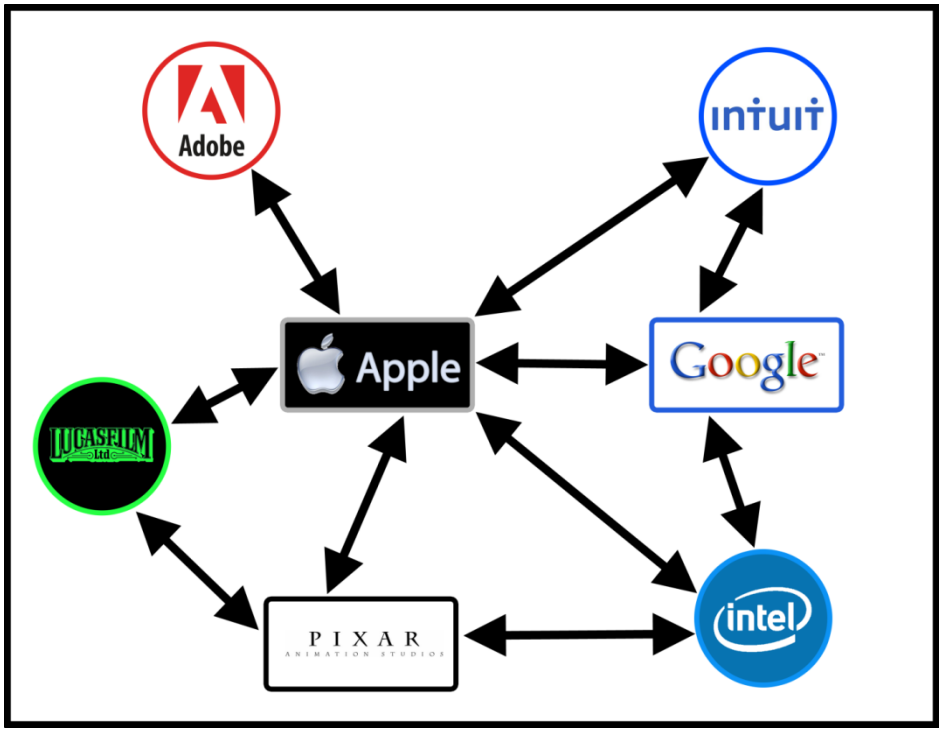
[24] See ADOBE_001096-097 and 231APPLE002145 (Adobe-Apple); PIX00003419 (Apple-Pixar); 231APPLE002140 and 231APPLE073139 (Apple-Google); GOOG-HIGH TECH-00008281-284 (Google-Intel); GOOG-HIGH TECH-00008342-350 (Google-Intuit); and Deposition of James Morris, August 3, 2012 at p. 93 (Lucasfilm-Pixar).

[25] These dates are based on the notice send to a party to the alleged agreement. I understand that Apple and Google each received a Civil Investigative Demand ("CID") on March 13, 2009. Pixar received a CID on May 27, 2009.

[26] See PIX00015306 (Intel agreed with Pixar that it "will not proactively pursue any Pixar employee going forward.") The agreement also included a no-hire without permission provision that prohibited Intel from hiring Pixar employees, regardless of whether a Pixar employee contacted Intel first, unless the head of Pixar

Intel, Intuit, and Lucasfilm that mirrored Apple's agreements with Adobe, Pixar, and Google.[27]

Figure 2: Relationships of the Alleged Agreements Among Defendants



23. All of the Non-Compete Agreements covered all employees of the respective companies, regardless of employee geography, job function, product group, or time period. Each of the Agreements prohibited cold-calling, meaning that the parties agreed not to solicit each other's employees in any manner. This agreement applied to all recruiters who were either directly employed by or were

approved the hire. See also, 76577DOC000464 ("We cannot recruit (including calling up, emailing, or enticing in any way) current Pixar employees to come work for Intel. If a Pixar employee applies without being recruited by Intel, contact Pat Gelsinger [a Senior VP at Intel] and explain to him a Pixar employee (provide the candidates [sic] name) has applied to Intel without being recruited and he will contact the CEO of Pixar for approval to hire.").

[27] See 231APPLE041661 and 231APPLE041662 (Apple's "Hands Off (Do Not Call List)" included every Defendant).

headhunters hired by the agreeing firms.[28] Some of the agreements included additional terms, such as:

- Do not hire: The parties agreed not to make employment offers to employees of the other firm without specific approval from the current employer's chief executive.[29]
- Pre-notify: The parties agreed to notify each other prior to making an offer to hire an employee at the other firm.[30]
- No counteroffer. The initiating firm that makes an offer to an employee of the other firm agreed not to improve its initial offer if the offer was matched by the other firm.[31] In other words, "no bidding wars."[32]

24. The sections below describe each of the agreements among the seven Defendants as I understand them.

[28] See e.g., 231APPLE001164, GOOG-HIGH TECH-00023500-601 at 520-528., and PIX00000400.

[29] When present, this provision applied even when an employee initiated contact. See, e.g., 76577DOC000464. Even if certain agreements may not have begun with this express provision, they often operated in this manner in practice. For example, Pixar and Google sought Steve Jobs's permission before making offers to Apple employees. See PIX00006025; 231APPLE002151. Apple refused to consider Adobe employees unless they first left employment with Adobe. See 231APPLE080776 ("This is a response I received from an ADOBE employee who applied for a position through our job posting site. I called him to ensure he is still an ADOBE employee, explained our mutual agreement / guidelines, and asked that he contact me should his employment with ADOBE terminate, but at this time I am unable to continue exploring with him. . . . I do not want anything in 'writing'.") Apple also attempted to enter into a "no hire" agreement with Palm, which Palm's CEO Ed Colligan rejected. See PALM00005 – 008 at 006 and PALM00022 – 027 at 024. See also, 231APPLE002153 - 154, and 231APPLE002214.

[30] See e.g., PIX00000400; GOOG-HIGH TECH-00056790.

[31] See PIX00000400; LUCAS00009252.

[32] See PIX00004051 ("We just won't get into bidding wars" for employees.); LUCAS00013507 ("We have agreed we want to avoid bidding wars.").

1. Pixar-Lucasfilm

25. I understand that a Non-Compete Agreement existed between Pixar and Lucasfilm for many years, beginning well before the year 2000.[33] In addition to not Cold-Calling each other's employees, each company agreed to inform the other of any offer made to an employee of the other company pursuant to an unsolicited application made by the employee.[34] The agreements further specified that in the case of such an unsolicited application the company making the job offer would make only one offer, and would not improve it in response to a counter-offer by the employee's current employer.[35] The agreement covered all employees.[36] On May 27, 2009, the DOJ issued a Civil Investigative Demand ("CID") to Pixar.[37] I have been asked to assume the agreement ended on that date.

26. Jim Morris, Pixar's General Manager and former head of Lucasfilm's Industrial Light and Magic division, described the agreement as follows in a videotape created on December 9, 2008: "We have an anti-poach clause between the Lucas companies and -- and this company. We don't -- we don't recruit from one another, we don't call -- if the people want to go from one company to the other, we, you know, find a way to let that happen. But we have a -- sort of a gentleman's agreement that we've honored pretty well here for the last many years."[38]

27. The "gentleman's agreement" concerned all employees of the companies, had no geographic limit, and had no expiration date.[39] Pixar and Lucasfilm provided

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[33] See Deposition of Lori McAdams, August 2, 2012 at p. 127:4-16 ("Well, I was at Lucasfilm from 1984 through 1998, and that understanding was in place at that time."); p. 132:15 ("[The agreement] had always been there.") and Deposition of James Morris, August 3, 2012 at p. 931.

[34] PIX00002328-329 at 328 and PIX00000038-039; PIX00000400 and PIX00006057.

[35] PIX00002328-329 at 328; PIX00000400.

[36] PIX00002328-329 at 328.

[37] See PIX00001958.

[38] See Deposition of Jim Morris, August 3, 2012 at p. 113:10-16.

[39] See Deposition of Jim Morris, August 3, 2012 at pp. 126:20-127:10; Deposition of Lori McAdams, August

the written terms of the agreement to management and certain senior employees with relevant hiring or recruiting responsibilities.[40]

28. It appears the companies abided by this agreement[41] and viewed it as important to avoid competing for each other's workers.[42]

29. The executives of these firms also clearly viewed containing labor costs as a major priority.[43]

30. Pixar's President Ed Catmull clearly understood the structural effect of competition on wages. As he observed in an email to a Disney executive: "Every time a studio tries to grow rapidly, it seriously messes up the pay structure . . . by offering higher salaries to grow at the rate they desire, people will hear about it and leave. We have avoided wars up here in Northern California because all of the companies up here – Pixar, ILM [Lucasfilm], Dreamworks, and a couple of smaller places – have conscientiously avoided raiding each other."[44]

2, 2012 at p. 160:23-25. See also, Deposition of Donna Morris, August 21, 2012 at pp. 226:22-227:5 and Deposition of Mark Bentley, August 23, 2012 at pp. 17:21-18:2.

[40] See Deposition of Lori McAdams, August 2, 2012 at p. 145:5-17; PIX00002262-64 ("I created it [summary of no-solicitation agreement] to give to the recruiting team so they would know what the gentleman's agreement was.").

[41] Deposition of Lori McAdams, August 2, 2012 at pp. 149:17-151:17 (PIX0009416); pp. 135:12-137:1 (PIX00003640).

[42] Deposition of Lori McAdams, August 2, 2012 at pp. 135:12-139:1; PIX00003640 ("[T]hey got really mad that we hired Rob Rieders.").

[43] PIX00009216-217 at 217. ("I know you are adamant about keeping a lid on rising labor costs").

[44] PIX00000229.

2. The Apple Non-Compete Agreements

a. Adobe

31. As of May 2005, the CEOs of Apple and Adobe had entered into an agreement that their respective companies would not recruit each other's employees.[45] This agreement covered all employees.[46] Apple placed Adobe on its "Do Not Call" list and Adobe placed Apple on its "Companies that are off limits" list, both of which instructed recruiters not to solicit employees from the listed companies and to inform each other if senior executives of each company were actively seeking employment at the other.[47] On March 13, 2009, the DOJ issued CIDs to Apple and Adobe.[48] I have been asked to assume the agreement ended on that date.

32. On May 26, 2005, Steve Jobs complained to Adobe CEO Bruce Chizen that Adobe was recruiting Apple employees.[49] Chizen responded, "I thought we agreed not to recruit any senior level employees … I propose we keep it that way. Open to discuss. It would be good to agree."[50] Jobs replied: "OK, I'll tell our recruiters that they are free to approach any Adobe employee who is not a Sr. Director or VP. Am I understanding your position correctly?" Chizen appeared to recognize the threat and capitulated: "I'd rather agree NOT to actively solicit any employee from either company . . . If you are in agreement I will let my folks know." The next day, Adobe HR Vice President Theresa Townsley announced to her recruiting team, "Bruce and Steve Jobs have an

[45] 231APPLE002145.

[46] 231APPLE002145.

[47] See 231APPLE001164 -165 and ADOBE_001096-097.

[48] See 231APPLE003695 and ADOBE_007392.

[49] See 231APPLE002143.

[50] See 231APPLE002143.

agreement that we are not to solicit ANY Apple employees, and vice versa."[51] Mr. Chizen forwarded Ms. Townsley's email to Steve Jobs. [52]

33. I understand that the two firms abided by the agreement.[53]

34. To ensure compliance with the agreement, Apple instructed its recruiting personnel to adhere to the agreement.[54] Adobe, in turn, placed Apple on its "Companies that are off limits" list, which instructed Adobe employees not to cold call Apple employees.[55]

b. Google

35. I understand that by February 2005 Apple and Google agreed that the two companies would not "cold call" each other's employees.[56] The agreement covered all employees.[57] Apple placed Google on its "Do Not Call" list and Google placed Apple on its "Do Not Cold Call" list, both of which instructed recruiters not to solicit employees from the listed companies.[58] On March 13, 2009, the DOJ issued CIDs to Apple and Google.[59] I have been asked to assume the agreement ended on that date.

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[51] See 231APPLE002145 (emphasis in original).

[52] See 231APPLE002145.

[53] See ADOBE_001095.

[54] 231APPLE002145 ("Please ensure all your worldwide recruiters know that we are not to solicit any Adobe employee."); 231APPLE080776-777 (Apple recruiter tells Adobe applicant that she cannot consider him until he leaves Adobe, even though "the agreement is not to 'poach' candidates, that meaning that if you directly apply to Apple, there should be no issue."); ADOBE_007186 ("Apple would be a great target to look into, unfortunately Bruce and Steve Jobs have a gentleman's agreement not to poach each other's talent . . . .").

[55] See ADOBE_00421-422.

[56] See 231APPLE002140 and 231APPLE073139. See also, GOOG-HIGH TECH-00008002-005 at 004.

[57] GOOG-HIGH TECH-00008002-005 at 004.

[58] See GOOG-HIGH TECH-00008002-005 and GOOG-HIGH TECH-00023500-601 at 520-521.

[59] See 231APPLE003695 and GOOG-HIGH TECH-00024585.

36. On February 18, 2005, Intuit Chairman and Apple Board Member Bill Campbell reached out to Google CEO Eric Schmidt regarding Google's recruitment of Apple employees.[60] Mr. Campbell reported back to Steve Jobs: "Eric told me that he got directly involved and firmly stopped all efforts to recruit anyone from Apple."[61] That same day, Apple's head of HR Danielle Lambert reported to her recruiting staff: "Please add Google to your 'hands-off' list. We recently agreed not to recruit from one another so if you hear of any recruiting they are doing against us, please be sure to let me know. Please also be sure to honor our side of the deal."[62]

37. Later that year, Arnnon Geshuri, Google's head of recruiting, was asked to create a formal "Do Not Cold Call" list regarding companies, including Apple, that had "special agreements" with Google to eliminate Cold-Calling. The draft was presented to Google's Executive Management Group ("EMG"), a committee consisting of Google's senior executives, including Eric Schmidt, Larry Page, Sergey Brin, and Shona Brown (Google's head of HR). Mr. Schmidt approved the list.[63] Mr. Geshuri added or removed a company from Google's Do Not Call when instructed to do so by a member of the EMG.[64]

38. Once the EMG approved it, Mr. Geshuri formalized the "Special Agreement Hiring Policy: Protocol for 'Do Not Cold Call' and 'Sensitive' Companies," and ensured that all of Google's hundreds of recruiters adhered to its terms.[65]

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[60] See 231APPLE002140.

[61] See 231APPLE002140.

[62] See 231APPLE073139.

[63] See GOOG-HIGH TECH-00007725 (Mr. Geshuri sent the draft "Do Not Call" list to Ms. Brown, who responded: "I would like to finalize with you Monday AM, and then present in EMG . . . ."; GOOG-HIGH TECH-00007731 (Mr. Schmidt approved the list on October 4, 2005: "This looks very good."); Deposition of Arnnon Geshuri, August 17, 2012 at pp. 161:2-167:8.

[64] Deposition of Arnnon Geshuri, August 17, 2012 at p. 172:6-8 (Q: And who would tell you whether to put a company on or off of the do-not-call list? A: It was usually an EMG member.")

[65] GOOG-HIGH TECH 00008283 and GOOG-HIGH TECH-00008342 (example iterations of the Do Not Call list); Deposition of Arnnon Geshuri, August 17, 2012 at p. 170:19-22 ("I made sure the team was -- was definitely aware of this protocol"); Deposition of Arnnon Geshuri, August 17, 2012 at pp. 43:20-44:10 (from

39. I have reviewed evidence of specific instances in which both firms adhered to the agreement.[66] In one case, compliance meant terminating a Google recruiter who violated the agreement.[67] Google referred to this kind of enforcement as an "Eric [Schmidt] firedrill."[68]

c. Pixar

40. In April 2007 the directors of human resources for Apple and Pixar agreed to a Non-Compete Agreement that mirrored the terms of the agreement between Lucasfilm and Pixar.[69] Apple placed Pixar on its "Do Not Call" list, which instructed recruiters not to solicit employees from the listed companies, and Pixar instructed its human resource personnel to abide by the agreement.

41. I understand that historically Pixar and Apple restricted employees from moving from one company to another during the period of time when Steve Jobs was an executive of Apple and a direct owner of Pixar. On March 13, 2009, the DOJ issued a CID to Apple.[70] I have been asked to assume the agreement ended on that date.

42. Beginning no later than 2004, Pixar sought Steve Jobs' permission before making an offer of employment to an Apple employee, regardless of whether

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2004 to 2009, Mr. Geshuri grew Google's recruiting operations from 40 recruiters to 900, which allowed Google to hire at a rate of "[redacted] people a week.").

[66] See 231APPLE002149; GOOG-HIGH TECH-0007574-576.

[67] GOOG-HIGH TECH-00009454; GOOG-HIGH TECH-00000107 (In an email in which Mr. Schmidt was copied: Mr. Geshuri: "the sourcer who contacted this Apple employee should not have and will be terminated within the hour. We are scrubbing the sourcer's records to ensure she did not contact anyone else." Ms. Brown: "Appropriate response. Please make a public example of this termination with the group. Please also make it a very strong part of new hire training for the group. I want it clear that we have a zero-tolerance policy for violating our policies. This should (hopefully) prevent future occurrences."); Deposition of Arnnon Geshuri, August 17, 2012 at pp. 214:7-215:20.

[68] GOOG-HIGH TECH-00023106 and GOOG-HIGH TECH-0024458; Deposition of Arnnon Geshuri, August 17, 2012 at pp. 255:3-260:14.

[69] At the time of these agreements Steve Jobs was the largest shareholder of Walt Disney, to which he had sold Pixar in 2006 and he sat on Disney's board of directors. See PIX00003978.

[70] See 231APPLE003695.

the Apple employee applied to Pixar without being solicited. For example, on February 8, 2004, Rob Cook, Pixar's Vice President of Software Engineering, wrote to Steve Jobs: "Steve, an Apple employee applied for the job of project coordinator, which is basically an administrative assistant to our project managers. . . . Would it be OK for us to make her an offer?" Steve Jobs responded: "Yea, it's fine." Mr. Cook forwarded Steve Jobs's email to Mr. Catmull, who responded: "The key is to stay away from the engineers."[71] Ten days after this exchange, Mr. Catmull emailed Steve Jobs regarding entering into a no-recruit agreement to eliminate competition with Sony: "our people are become [sic] really valuable and we need to nip this in the bud."[72] The next year, in November 2005, Pixar recruiter Howard Look stated that Pixar was struggling to find candidates, but "of course cannot recruit out of Apple."[73]

43. On April 30, 2007, Apple and Pixar formalized their understanding and expanded it to all employees with a call between Ms. McAdams of Pixar and Danielle Lambert, Apple's head of HR. Apple and Pixar modeled their agreement on the "gentlemen's agreement" Pixar had with Lucasfilm. Ms. McAdams told her recruiting team about the "Apple Gentleman's agreement": "I just got off the phone with Danielle Lambert, and we agreed that effective now, we'll follow a gentlemen's agreement with Apple that is similar to our Lucasfilm agreement. That is . . . we won't directly solicit any Apple employee (including outside recruiters if we use them) . . . Danielle will ask her Recruiting team to follow the same procedure . . . ."[74]

44. After entering into the agreement, senior executives of both Pixar and Apple monitored compliance and policed violations. For example, Lori McAdams testified that Steve Jobs got angry if Pixar hired an Apple employee.[75] When

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[71] See PIX00006025.

[72] See PIX00006023.

[73] See PIX0003600.

[74] See PIX00004883; emphasis added; Deposition of Lori McAdams, August 2, 2012 at pp. 182:5-183:9.

[75] See Deposition of Lori McAdams, August 2, 2012 at p. 159:4-9.

asked whether Pixar would consider hiring an Apple employee who had expressed interest in Pixar, Ed Catmull replied, "[Steve] will want the name of the guy. My guess is that Steve will approve it if he knows that he is going to lose him, but we would have to go through the step of Apple knowing what was happening."[76] To ensure compliance with the agreement, Pixar instructed its human resources personnel to adhere to the agreement and to preserve documentary evidence establishing that Pixar had not actively recruited Apple employees.[77] Apple, in turn, placed Pixar on its internal "Do Not Call List," which instructed Apple employees not to cold call Pixar employees.[78]

3. The Google Non-Compete Agreements

a. Apple

45. Google's Non-Compete Agreement with Apple is described above.

b. Intel

46. Effective March 6, 2005, Google and Intel entered into a Non-Compete Agreement.[79] Multiple documents confirm this agreement.[80] The agreement covered all Google and Intel employees. Google placed Intel on its "Do Not Cold Call" list, which instructed recruiters not to solicit employees from the listed companies, and Intel instructed its human resource personnel to abide by the agreement. On March 13, 2009, the DOJ issued a CID to Google.[81] I have been asked to assume the agreement ended on that date.

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[76] PIX00002210.

[77] PIX0003629-630.

[78] See 231APPLE042669 and 231APPLE041662.

[79] See GOOG-HIGH TECH-00008281-284 at 283.

[80] See 76556DOC000003, 76614DOC010212, 76526DOC000007, 76526DOC000011, and GOOG-HIGH TECH-00056879.

[81] See GOOG-HIGH TECH-00024585.

47. On April 16, 2007, Intel C.E.O. Paul Otellini wrote to an Intel recruiter, "I have an unofficial no poaching policy with [Google.]"[82] On June 4, 2007, Eric Schmidt wrote Otellini re "hiring": "I checked as to our recruiting policy with Intel. 'Intel has been listed on the Do Not Call List since the policy was created. No one in staffing directly calls, networks, or emails into the company or its subsidiaries looking for talent.' Hopefully there are no exceptions to this policy and if you become aware of this please let me know immediately!"[83] Otellini forwarded the email to Patty Murray, Intel's Senior Vice President and Director of HR: "FYI . . . . Do not fwd."[84]

48. Google's formal "Do Not Cold Call" list included Intel along with Apple, as "companies [that] have special agreements with Google," and states the same "Effective" date for both Apple and Intel: "March 6, 2005."[85]

49. The agreement was enforced by the chief executives of the two companies. Intuit's Chairman, Bill Campbell, was also apparently involved in the agreement between Google and Intel. For example, in August of 2006, Campbell reached an agreement with Google's Jonathon Rosenberg (Google's Senior Vice President of Product Management) that Google should impose additional restrictions beyond no solicitation: they agreed that Google would call Otellini before making an offer to an Intel employee, regardless of whether the Intel employee first approached Google.[86]

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[82] See 76526DOC000007.

[83] See 76614DOC010212.

[84] Two days later, in an email titled "global gentleman agreement with Google," an Intel recruiter asked Otellini and another senior executive, "Are either of you aware of any agreement with Google that prohibits us from recruiting Google's senior talent?" See 76526DOC000011. Otellini replied, "Let me clarify. We have nothing signed. We have a handshake 'no recruit' between eric and myself. I would not like this broadly known." See 76526DOC000011.

[85] GOOG-HIGH TECH-00008281-284 at 283; GOOG-HIGH TECH-00056879 ("Since the beginning of the Do Not Call List, Intel has been listed.").

[86] GOOG-HIGH TECH-00056790 (Rosenberg: "Campbell and I already discussed this [talking to Intel before making an offer to an Intel employee] and agreed that either way [whether Intel was treated as a "Do Not Call" company, or a "sensitive" company] I should give a courtesy call to Paul Otellini. I'm meeting with

c. Intuit

50. In June 2007, Google and Intuit entered into a Non-Compete Agreement between Google and Intuit.[87] The agreement also covered all employees. Google placed Intuit on its "Do Not Cold Call" list, which instructed recruiters not to solicit employees from the listed companies, and Intuit instructed its human resource personnel to abide by the agreement. On March 13, 2009, the DOJ issued a CID to Google.[88] I have been asked to assume the agreement ended on that date.

51. On June 6, 2007, Google Recruiting Director Arnnon Geshuri wrote Eric Schmidt: "During a brief conversation with Shona and Bill Campbell, Bill requested that Intuit be added fully to the Do Not Call list. Currently, our non-solicit policy only covers 18 Intuit employees . . . The change to our Do Not Call policy will make our hands-off approach to Intuit explicit and ensure clarity."[89] By June 12, 2006, Intuit was added fully to the list.[90]

52. I have reviewed specific evidence of enforcement of the agreement, including enforcement by Campbell himself.[91]

[the Intel candidate] tomorrow and I will ask him how he wants to handle communication to Intel management before we even get to the stage of specifically discussing an offer.").

[87] See GOOG-HIGH TECH-00009764. There is some indication an agreement may have existed earlier. In May 2006, Google employees discussed possibly contacting a candidate from Intuit, finally deciding that "would effectively be a cold call, so I'll ask martha j not to contact him." GOOG-HIGH TECH-00007696 – 697 at 696.

[88] See GOOG-HIGH TECH-00024585.

[89] GOOG-HIGH TECH-00009764.

[90] GOOG-HIGH TECH-00007715; GOOG-HIGH TECH-00009391 ("please update the DNC list to now include Intuit 100% do not call.").

[91] GOOG-HIGH TECH-00057458. See also, GOOG-HIGH TECH-00058235 (email from Bill Campbell to Google HR Director Lazlo Bock asking "Can we please not target Intuit").

4. *Department of Justice Investigation and the End of the Collusion*

53. On June 3, 2009, the New York Times published an article indicating that the DOJ had begun an investigation into the Defendants' hiring practices and the alleged Non-Compete Agreements in particular.[92] I understand that by the end of March 2009, the DOJ had informed the defendants of the investigation. I have assumed for this analysis that, as of that date the agreements between the defendants ceased to have an effect on their recruiting and hiring activities.

C. Named Plaintiffs

54. As described above, I have been asked to consider the effect of the Non-Compete Agreements on the All-Employee Class of salaried employees (and the Technical Employee Class). The members of each proposed class worked for a Defendant at a time when that Defendant was a party to at least one such Agreement (excluding retail employees, corporate officers, members of the boards of directors, and senior executives).

[92] Helft, Miguel, "Unwritten Code Rules Silicon Valley Hiring," The New York Times, June 3, 2009, http://www.nytimes.com/2009/06/04/technology/companies/04trust.html?_r=1.

Figure 3: Class Employee Summary

Defendant	Agreement Period	Number of Class Members	Total Class Compensation (Dollars)
(1)	(2)	(3)	(4)
Adobe	05/05-03/09	7,056	$ 3,035,176,142
Apple	02/05-03/09	[redacted]	[redacted]
Google	02/05-03/09	[redacted]	[redacted]
Intel	03/05-03/09		
Intuit	06/07-03/09	7,186	2,081,658,505
Lucasfilm	01/01-03/09	[redacted]	[redacted]
Pixar	01/01-03/09		
TOTAL		**109,048**	**$ 52,047,039,447**

Note: Columns (3) and (4) are calculated using the Class Periods described in Paragraphs 8 and 9, above.

Source: Defendants' employee compensation data; SEC filings.

Figure 4: Technical Employee Class Summary

Defendant	Agreement Period	Number of Class Members	Total Class Compensation (Dollars)
(1)	(2)	(3)	(4)
Adobe	05/05-03/09	3,601	$ 1,740,210,006
Apple	02/05-03/09	[redacted]	[redacted]
Google	02/05-03/09	[redacted]	[redacted]
Intel	03/05-03/09	[redacted]	[redacted]
Intuit	06/07-03/09	3,236	1,006,035,578
Lucasfilm [1]	01/01-03/09	[redacted]	[redacted]
Pixar	01/01-03/09		
TOTAL		**59,550**	**$ 32,848,992,686**

Note: Columns (3) and (4) are calculated using the Class Periods described in Paragraphs 8 and 9, above.

[1] Missing job title information for 2005.

Source: Defendants' employee compensation data; SEC filings.

55. I understand the following named plaintiffs are seeking to serve as class representatives for the proposed All-Employee Class or Technical Employee Class :

a. Michael Devine who worked for Adobe from October 2006 through July 7, 2008 as a computer scientist for Adobe Systems;

b. Mark Fichtner who worked for Intel as a software engineer from May of 2008 through May 2011;

c. Siddharth Hariharan who worked for Lucasfilm as a software engineer from January 8, 2007 through August 15, 2008;

d. Brandon Marshall, who worked for Adobe as a software production quality specialist from July 2006 through December 2006; and

e. Daniel Stover, who worked for Intuit as a Web Marketing Representative, Web Developer, and Software Engineer from July 2006 through December 2010.

56. I have summarized the employment histories of these individuals as contained in Defendants' data. The employment histories of the five named plaintiffs are reported in Figure 5.

Figure 5: Named Plaintiffs' Employment Histories

Name Plaintiff's Employment Profile Summary

Name	Year	Employer	Title	Hire Date	Separation Date	Base Annual Salary	Supplemental Compensation[1]
						(Dollars)	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daniel Stover	2006	INTUIT	WEB MARKETING REP 2	10/30/2006		$ 75,000	$ 4,129
	2007	INTUIT	WEB DEVELOPER 2	10/30/2006		83,500	19,765
	2008	INTUIT	SOFTWARE ENGINEER	10/30/2006		91,300	83,877
	2009	INTUIT	SW ENGINEER 2	10/30/2006	12/3/2009	94,000	38,553
Brandon Marshall	2006	ADOBE	SW PROD QUALITY SPEC 1	7/31/2006	12/9/2006	68,000	5,895
Mark Fichtner	2001	INTEL	SOFTWARE ENGINEER, SR	7/12/1993		84,250	67,461
	2002	INTEL	SOFTWARE ENGINEER, SR	7/12/1993		84,250	40,176
	2003	INTEL	SOFTWARE ENGINEER, SR	7/12/1993		84,250	25,101
	2004	INTEL	SOFTWARE ENGINEER	7/12/1993		86,782	36,592
	2005	INTEL	SOFTWARE ENGINEER	7/12/1993		95,132	38,299
	2006	INTEL	SOFTWARE ENGINEER	7/12/1993	11/8/2006	100,362	48,189
	2008	INTEL	SOFTWARE ENGINEER	7/12/1993		108,000	14,013
	2009	INTEL	SOFTWARE ENGINEER	7/12/1993		108,000	30,501
	2010	INTEL	SOFTWARE ENGINEER	7/12/1993		110,160	42,078
	2011	INTEL	SOFTWARE ENGINEER	7/12/1993	6/1/2011	111,290	35,973
Michael Devine	2006	ADOBE	COMPUTER SCIENTIST, SW DEV 4	9/25/2006		110,000	21,222
	2007	ADOBE	COMPUTER SCIENTIST, SW DEV 4	9/25/2006		113,135	33,405
	2008	ADOBE	COMPUTER SCIENTIST, SW DEV 4	9/25/2006	7/8/2008	118,226	3,445
Siddharth Hariharan	2007	LUCASFILM	SOFTWARE ENGINEER	1/8/2007		85,000	17,000
	2008	LUCASFILM	SOFTWARE ENGINEER	1/8/2007	8/15/2008	88,335	-

[1] Supplemental compensation includes bonus, overtime compensation, options values and restricted stock values

Source: Defendants' employee compensation data; SEC filings

D. Background on Defendants' Recruiting and Hiring Practices

57. Defendants classified potential job candidates as either "passive" or "active."[93] Active candidates were searching for employment and could be expected to discover posted opportunities (e.g., an active candidate might apply through the company's website). Passive candidates were not searching for new

[93] 76550DOC000014-095 at 024, LUCAS00013673-703 at 683, GOOG-HIGH TECH-00039446-581 at 451 and 76566DOC000005-026 at 010.

opportunities but might be interested if the candidate learned of a good job opportunity.[94]

58. The Defendants used several types of methods for uncovering (or "sourcing"[95]) passive candidates, including referrals.[96] The initial contact to a passive candidate is called "Cold-Calling."

59. Many companies, including the Defendants, actively pursue Cold-Calling strategies. For example, the Competitive Intelligence Group at Google created a "Product Matrix," profiling competitors and highlighting areas in which these competitors have employees that would be useful to Google, naming Cold-Calling as a method to "strategically reach, engage and close the best talent in the world."[97]

60. Intuit recruiters were expected to use Cold-Calling as a recruiting technique.[98] Google identified Cold-Calling as an activity of its recruiters ("sourcers").[99]

61. In preparation for Cold-Calling, the Defendants profiled their competitors, looking for job categories and titles that corresponded to the positions to be filled.[100] Cold-Calling recruiters would then approach employees who fit into those categories to determine their potential interest, which could be followed

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[94] Deposition of Donna Morris, August 21, 2012 at pp. 106:22-107:19 and Exhibit 212.

[95] Intel defined sourcing as, "the identification and uncovering of candidates through proactive recruiting techniques." Sourcing channels included complex internet searches, networking, job fairs and searching through previous applications. Companies can also use external recruiting agencies to find potential candidates 76550DOC000014-095 at 19 and 23 and 76545DOC000021-051 at 23.

[96] 76550DOC000014-095 at 023 and LUCAS00004690 at 692-694.

[97] GOOG-HIGH-TECH-00054775.

[98] See INTUIT_001661-664 at 663.

[99] See GOOG-HIGH TECH-00007950-973 at 971.

[100] See GOOG-HIGH-TECH-00055116 and GOOG-HIGH-TECH-00055413-414.

by offers of higher compensation (sometimes in the form of signing bonuses) to entice them away from their current companies.[101]

62. The Defendants viewed Cold-Calling as an important means of competing for workers. Cold-Calling is a pro-active approach to elicit responses from already-employed persons who might not respond to other forms of recruiting.[102] High technology companies like each of the Defendants can be particularly interested in potential employees who are not seeking a change of employment because:

- Employees who are content and not actively looking for opportunities elsewhere are perceived to be more qualified, diligent and reliable.[103]
- Such employees have training and on-the-job experience, and therefore can save the hiring company training costs.[104]
- These potential hires may have established track records, making it easier to identify the highest-performing individuals, and therefore saving the hiring company the costs of unsuccessful trial employees.[105]
- Hiring employees away from competitors deprives rivals of valuable assets.

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[101] PIX00002349-425 at 406, LUCAS00004446-452 at 448, GOOG-HIGH-TECH-00054905-913 (Talking points against [redacted]) at 905 "Bonus is better at [redacted]" and at 912 "equity comp is typically better at [redacted] (comparing against [redacted])" and Emphasizing GSU vesting schedule against [redacted] and [redacted] and GOOG-HIGH-TECH-00038103-128 at 112.

[102] For example, ADOBE_002773-002798 at 785 "Focus on 'passive' talent"'… "top performers tend to be entrenched, 'heads down' may be 'willing to listen' if the right opportunity is presented." Also see INTUIT_003008-010 at 010 and 76566DOC000085-098 at 092.

[103] "Passive sourcing will play an increasingly larger role in recruiting as we move forward as a company - Efficient and effective sourcing organization critical to acquire top talent in current market landscape" GOOG-HIGH TECH-00024149-218 at 152 and Deposition of Donna Morris, August 21, 2012 at pp.56:16-57:20.

[104] See, e.g., LUCAS00013705-773 at 728 (Oct. 19, 2006 Board of Directors Meeting: Under "Retention": "Revolving door; Lucasfilm has become the training ground for entertainment community"; "Recruiting and training is very expensive; need to increase talent tenure to get a reasonable return on our investment"; "Need to create strategies to keep people here").

[105] Deposition of Donna Morris, August 21, 2012 at pp. 90:25-91:10.

- Some employers may have failed to anticipate improvements in market conditions and may have left valuable employees with compensation packages far below what they could get elsewhere. This can create clusters of low-hanging fruit.

IV. Common Evidence and Analysis Are Capable of Showing that the Non-Compete Agreements Artificially Reduced the Compensation of Defendants' Salaried Employees

63. Methods and evidence, common to each Class as a whole, are capable of demonstrating that the Non-Compete Agreements reduced the compensation of All-Employee Class and Technical Employee Class members employed by the Defendants. This Class-wide proof of impact comes in two steps. First, there is abundant evidence, common to All-Employee Class and Technical Employee Class members, capable of showing that the Non-Compete Agreement suppressed the compensation of the members of the All-Employee Class and Technical Employee Class, generally. Such Class-wide methods and evidence include, without limitation: (a) standard economic theory regarding the effects of information asymmetries on labor market contracts, which work to the disadvantage of the less informed party, and (b) standard economic theory regarding the effects of movement of employees between firms enticed by better compensation, and the consequent interest of firms in peremptory increases in compensation to employees when poaching by key rivals occurs regularly; (c) multiple regression analyses, using extensive compensation data, showing that compensation was reduced for Class and Technical Employee Class members; and (d) documentary evidence, including documents from Defendants' own files, describing, *e.g.*, the Non-Compete Agreements, Defendants' enforcement of those Agreements, the importance of the Agreements, and the effects of poaching on movement between firms and compensation.

64. I have found further that Class-wide methods and evidence are capable of demonstrating that the Non-Compete Agreements suppressed the compensation of all or virtually all members of the All-Employee Class and Technical Employee Class. In addition to the Class-wide evidence described in

the previous paragraph, such common proof that the effects of the Non-Compete Agreements was broadly felt also includes (a) economic theory regarding the interest of firms in fostering a concept known in the economic literature as "internal equity," such that compensation tracks the success of the firm's most highly compensated employees; (b) additional evidence that compensation of employees tended to move together over time, such that the effects of Non-Compete Agreements are likely to be broadly felt; and (c) evidence from Defendants' own files showing their respective concerns about preserving internal equity, as well as other documentary evidence, when Agreements were not in place, that some Defendants responded to periods of intense poaching by close rivals with across the board salary increases to all employees.

65. I describe these methods and evidence in greater detail below.

A. Class-wide Evidence is Capable of Showing that the Non-Compete Agreements Suppressed Compensation Generally

1. *Economic Theory Offers a Classwide Basis for Linking Non-Compete Agreements to* Suppressed Compensation Incurred by Members of the All-Employee Class and Technical Employee Class

66. There are three economic frameworks[106] that are particularly useful for evaluating the likely impact on employees of illegal agreements to suppress Cold-Calling. These frameworks--each well-accepted in the economics literature--explain various mechanisms by which anti-Cold-Calling agreements can suppress worker compensation generally.

67. The frameworks for considering the effect of the alleged non-compete agreements discussed below are (1) price discovery, (2) worker compensation equity and (3) profit-sharing. Each framework has different implications regarding the way in which the effects are spread across firms, across job

[106] "Frameworks" refers to general views regarding how labor markets function and "model" refers to a specific example of a framework. A framework is usually communicated in words, while a model is expressed with either graphs or mathematical formulae.

categories within firms and across time. The frameworks are not mutually exclusive in that effects of the Agreements can arise through multiple channels. In this section, I will focus here on frameworks "(1)" and "(3)" as they pertain mainly to the general linkage between the Non-Compete Agreements and suppressed compensation. I will elaborate on framework "(2)" regarding internal equity when I discuss the Class-wide evidence capable of showing widespread harm to the either class later in my Report.

68. For all three frameworks, Cold-Calling is part of the information gathering that reveals the nature of outside opportunities both to workers and to employers. Anti-Cold-Calling agreements suppress compensation by limiting this flow of information about attractive outside opportunities.

69. Cold-Calling is an especially important source of information about outside opportunities under two circumstances: (a) uneven growth (i.e., firms are growing at different rates), which requires reallocation of the workforce in favor of the firms which can offer workers the best contracts, and (b) even growth (firms are growing at a generally equal rate), which doesn't necessitate any reallocation of the workforce but which creates greater competition for the scarce workforce.

70. Under either condition, Cold-Calling contributes to economic efficiency. With uneven growth, Cold-Calling helps to assure that workers are assigned to their most valued tasks. With even growth, Cold-Calling helps to assure that workers receive a proper scarcity premium which signals to other workers which skills are most needed. In both circumstances, economic theory predicts that agreements restricting Cold-Calling would suppress worker compensation for all or nearly all employees of the Defendants who agreed to them.

a. Price Discovery Framework

71. The market equilibrium models that economists often use presume that market forces are powerful enough and work rapidly enough that virtually all transactions occur at approximately the same price – the "market price" which equilibrates supply and demand. In reality, in the face of changed market conditions, the actual transactions' prices can deviate from the market

equilibrium sometimes by large amounts for long periods of time. The process by which actual transactions prices move to market equilibrium values is called "market price discovery."

72. The speed at which the price discovery process operates is determined by the frequency at which buyers and sellers get together to haggle over the price, and by the rate at which information about the outcomes of those bargains, consummated or not, is dispersed among other potential buyers and sellers. Non-Compete Agreements that limit the bargaining between employers and employees thus slow down the price discovery process and affect each and every labor contract in the markets.

73. In some settings the price discovery process is so slow and imperfect that the concept of a "market equilibrium" is of limited value for understanding the sequence of actual transactions.[107] Labor markets that involve infrequent bargains and limited information flows can have very sluggish price discovery. High transaction costs and weak information flows create very illiquid labor services which are transferred via bilateral bargains, not via markets.[108] The expensive and time-consuming task of uncovering and valuing the unique features of workers slows down the price discovery process and allows many transactions to occur at prices far from market equilibrium levels.

74. High-tech jobs involve high costs for transactions including time, money and personal dislocation. These high transaction costs make transactions very infrequent and limit the number of workers actively seeking new employers.

75. The labor market also has weak information flows about specific jobs. Employees may rely mostly on "water-cooler talk" perhaps supplemented by Internet sources. Employers, on the other hand, often hire private consulting firms to provide aggregated information about "market" compensation. For

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[107] Stiglitz, Joseph, "Information and the Change in the Paradigm in Economics," *The American Economic Review*, Vol.92, No. 3 (June 2002), pp. 460-501.

[108] For related effects in a financial context, see e.g., Green, Richard C., Dan Li and Norman Schürhoff, "Price Discovery in Illiquid Markets: Do Financial Asset Prices Rise Faster Than They Fall?," Journal of Finance, Volume 65, Issue 5, pp. 1669–1702, October 2010.

employees, Cold-Calling is an important channel of information about outside opportunities. Absent Cold-Calling, many labor contracts are negotiated in unequal bargains between informed employers and uninformed employees.

76. Agreements that reduce the number of bilateral bargains further slow the price discovery process and affect the whole sequence of actual transactions.[109] Non-Compete agreements do not change the value of the work; they only help employers keep more of that value.

b. Relationship Framework: Firm-Specific Assets

77. Net revenues of high-tech intellectual service firms accrue to one of the two assets that drive value: the "brand" (the firm) or the workers. The division of the net revenues between the firm and the workers is determined by outside competition for workers, which pressures firms to pay their workers at least as much as the best outside offer.[110]

78. When firm-specific knowledge assets reside within the brains of workers, the movement of workers between firms is a form of "creative destruction" meaning that the increased value of the worker at the new job is offset by destruction of value at the old. This is economically inefficient unless the value of the asset created exceeds the value of the asset destroyed. If neither party to the new employment contract is incented to worry about the destruction, there will be too much destruction, the consequence of which is too little creation. A new employer is unconcerned about the "destruction" of the previous employer's asset, or likes it if it impairs a competitor. It is therefore essential for firms to form relationships that make workers sensitive to the asset destruction that would occur if they switched employees. This can be done by making them joint owners of the intellectual assets of the firm, through stock option plans

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[109] See Tappata, Mariano, "Rockets and Feathers Understanding Asymmetric Pricing," UCLA Job Market Paper, January 2006 and Yang, Huanxing and Ye, Lixin, "Search with learning: understanding asymmetric price adjustments," Ohio State University, August 2006.

[110] GOOG-HIGH-TECH-00193377-382, GOOG-HIGH TECH-00038103-128 at 125, PIX00000038-039 and LUCAS00004446-452 at 451-452.

and restricted stock grants. These plans can help limit movement of critical workers.

79. If firms have not created adequate incentives to assure worker loyalty, Cold-Calling can seriously threaten loss of the critical intellectual assets. In periods when demand for the critical workforce is weak, firms may feel little threat of loss of workers, and may let grants of stock options and restricted stocks recede. Firms may be surprised when the market starts to heat up again and they start to lose critical workers. A legal countermeasure to limit loss of the critical workers would be increased use of stock options and restricted stock grants. Management which prefers not to share ownership with their workforce may instead choose the countermeasure of anti-Cold-Calling agreements, even if it may be illegal.

80. Economic theory therefore predicts that agreements such as the Non-Compete Agreements artificially suppress employee compensation on a widespread basis. Furthermore, evidence common to all potential class members in this case can be used to confirm this predicted effect.

2. *Defendants' Internal Documents Provide Additional Class-wide Evidence Capable of Showing that the Non-Compete Agreements Artificially Suppressed Compensation*

81. The Defendants' internal documents can be used to confirm that company-wide prohibitions on recruiting would tend to artificially suppress the compensation of the members of the All-Employee Class and Technical Employee Class.

82. Documents reveal that the defendants would otherwise have been competing for employees.[111] In the absence of these agreements, Defendants would have cold called one another's employees.[112]

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[111] See e.g., ADOBE_005950 - 967 at 966 ("list of [nine] companies Adobe's Board of Directors benchmarks against from a compensation standpoint" include Google, Apple, and Intel; with regard to benefits, Adobe is in a "six horse race" with Google, Apple, Intel and two other companies); PIX00006023 ("Our people are becoming really desirable and we need to nip this in the bud."); GOOG-HIGH TECH-00023206-212 at 209 ("The Recruiting Wars: How To Beat Google To Tech Talent").

[112] See GOOG-HIGH TECH-00056840 ("Cold-Calling into companies to recruit is to be expected unless

83. Prior to the Agreements the Defendants were concerned with successful poaching by other firms—and particularly other Defendants. In an email discussing Adobe's policy toward Apple under the Agreements, Adobe's Bruce Chizen wrote, "… Knowing Steve, he will go after some of our top Mac talent like Chris Cox and he will do it in a way in which they will be enticed to come (extraordinary packages and Steve wooing)."[113]

84. Thus Defendants recognized that Cold-Calling and other forms of poaching had the potential to drive up the cost of specific employees. They also recognized that the effects of poaching would extend well beyond the employees directly approached by a cold-call. Pixar's top executive Ed Catmull noted, "we learned that the company that Zemeckis is setting up in San Rafael has hired several people away from Dreamworks at a substantial salary increase… every time a studio tries to grow rapidly… it seriously messes up the pay structure."[114]

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they're on our 'don't call' list."); GOOG-HIGH TECH-00053679-681 at 680 ("Over the 8 years of my executive search experience, I've worked with hundreds of clients. And for every search assignment, the first thing we do is to target the direct competitors of the respective clients."); ADOBE_001092-093 at 092 ("Apple would be a great target to look into. Unfortunately, Bruce and Steve Jobs have a gentleman's agreement not to poach each other's talent."); GOOG-HIGH TECH-00023132 (as soon as eBay and PayPal were removed from Google's Do Not Call list, "staffing is ready to pursue several hundred leads and candidates"); 76506DOC000773-990 at 845 (in an Intel presentation titled "Intel's Complete Guide to Sourcing," on the slide regarding "Cold-Calling": "Calling candidates is one of the most efficient and effective was to recruit."); LUCAS00005403-446 at 405 ("The Recruiting Strategy for LucasArts for the next 2-3 years must be focused on the passive candidate."); ADOBE_002773-788 at 775 (Adobe presentation regarding sourcing focused on "passive" candidates:" "top performers tend to be entrenched, 'heads down.'"); GOOG-HIGH TECH-00024149-218 at 152 (in a Google "Sourcing Diagnostic": "Passive sourcing will play an increasingly large role in recruiting as we move forward as a company."); and GOOG-HIGH TECH-00007729 (a year before entering into its first no-solicit agreement with Apple, Shona Brown wrote: "We have historically always allowed recruiters to find talent wherever it is – even when it is with key partners . . . or sensitive competitors . . . Which is the right answer."). In response to one of Mr. Geshuri's "periodic reminders" to his recruiters regarding the "Do Not Call list," a Google recruiter remarked in frustration: "I guess the candidates I have been sourcing from Burger King, Jiffy Lube and Der Wienerschnitzel are still fair game." See GOOG-HIGH TECH-00008249 and Deposition of Arnnon Geshuri, August 17, 2012 at pp. 262:4-264:13.

[113] ADOBE_001096-001097 at 097.

[114] PIX00000229. Also noting, "I know that Zemeckis' company will not target Pixar, however, by offering higher salaries to grow at the rate they desire, people will hear about it and leave. We have avoided wars up in Northern California because all of the companies up her – Pixar, ILM, Dreamworks, and a couple of smaller places- have conscientiously avoided raiding each other."

85. These documents indicate defendants saw a significant potential benefit from reducing or limiting this competition for employees (e.g., relating to the perceived impact of actual and potential poaching on compensation).

86. In contexts not covered by the non-compete agreements, the defendants regularly and openly used Cold-Calling to find new employees. For example, in an Intuit email, Intuit officials looking to fill a position discuss "good target companies to go after."[115]

87. Even during the period of agreements, the Defendants considered Cold-Calling a useful tool in recruiting employees from companies other than those participating in the Agreements.[116]

88. In November 2007, after agreement between Adobe and Apple was officially terminated, a Hiring Analysis from Adobe's Competitive Intelligence Group reported, "recruiting and retaining top talent will likely be more competitive to the extent that the high tech sector remains economically healthy… As Microsoft, Google and Apple dial-up the volume on attracting Adobe resources, what changes or new approaches would assist Adobe in retaining top talent?"[117]

3. Analysis of Defendants' Compensation Data Is Additional Class-wide Evidence Capable of Showing that the Compensation of All-Employee Class and Technical Employee Class Members Was Suppressed by the Non-Competition Agreements

89. My analysis of Defendants' compensation data is additional common evidence capable of showing that restricting Cold-Calling would artificially suppress employee compensation by impeding the price discovery process.

90. Compensation of new recruits compared with existing employees can reveal the price discovery process at work. If compensation of current workers were close

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[115] INTUIT_002372.

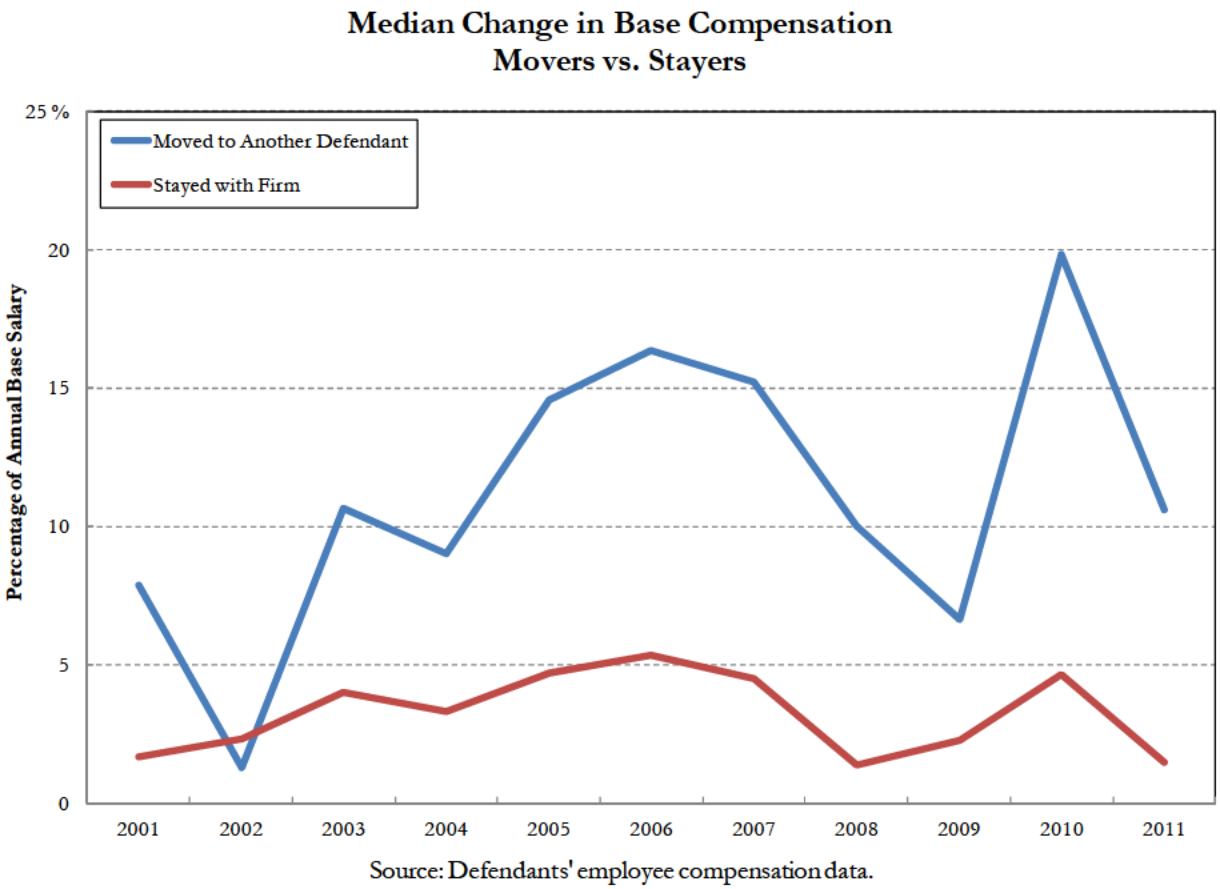
[116] See e.g., PIX00003610-00003611 at 610; GOOG-HIGH TECH-00008233 (6/21/2008 email' "actively recruiting key Yahoo! Employees was a recommended course of action given current industry dynamics").

[117] ADOBE_004964 – 004997 at 975.

to a "market equilibrium" level, the new recruits would be paid similarly to existing employees, net of "moving costs." If the market value of the workers were then to increase, that would set in motion a price discovery process during which new recruits were paid distinctly more than current employees with similar skills and experience. In the early phases of the price discovery process, the salaries of these new recruits might also be below equilibrium levels, and the compensation packages offered new recruits can improve over time in search of the higher equilibrium. As firms become aware of the increased external competition, compensation packages of current employees may be improved to bring them more in line with outside opportunities. It can take considerable time for this complicated price discovery process to find a new equilibrium in which new recruits and existing employees are paid about the same. It can take much longer if information about superior opportunities is suppressed by Non-Compete Agreements.

91. Thus, a symptom of price discovery at work would be better compensation packages for those who moved between Defendants than for those who stayed. In Figure 6 and Figure 7 below I compare on a year-by-year basis the percent changes in compensation of the movers versus the stayers--those who moved between Defendants and those who didn't. As Figure 6 shows, the increase in base salary of the movers was almost always above the stayers. But in 2006, the movers received almost 16 percent increases in base salary compared with about 5 percent for the stayers. That gap is a symptom of the price discovery process at work in search of higher wages, a process that was the apparent target of the anti-Cold-Calling agreements put in place at that time.

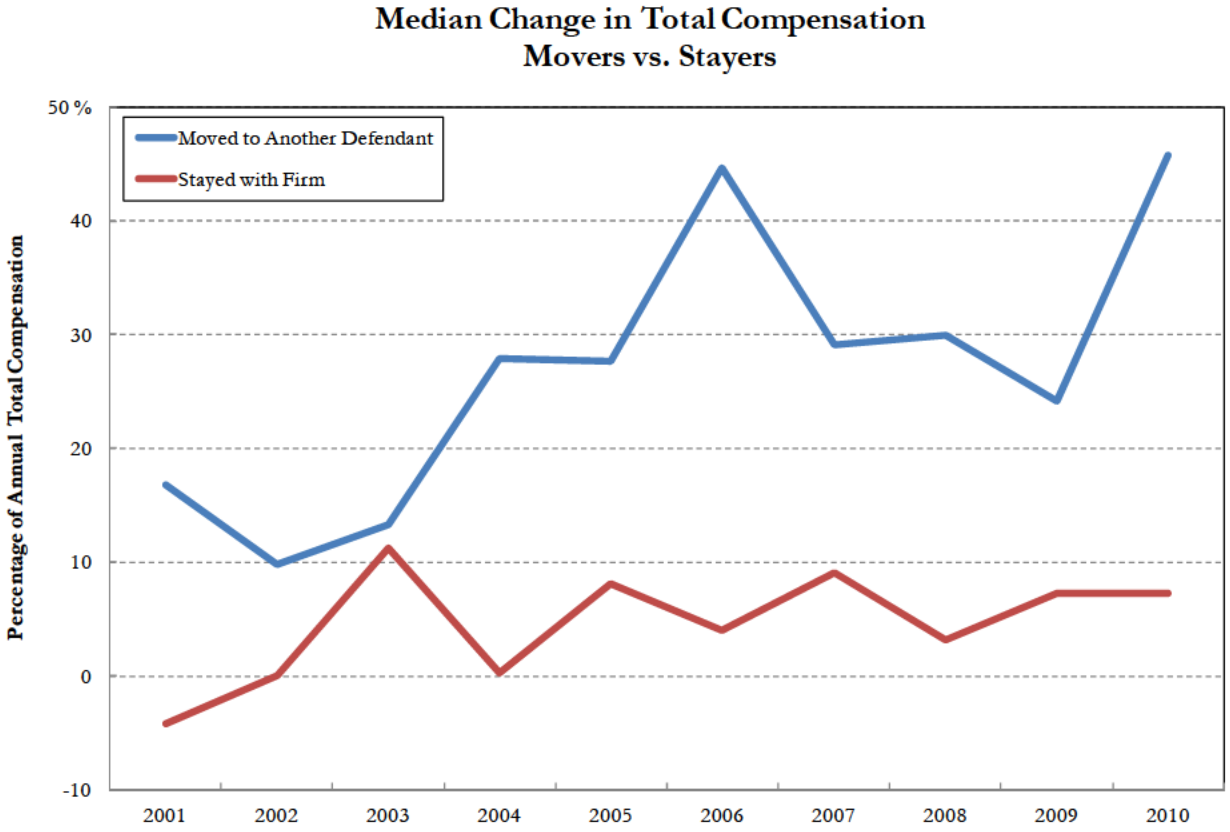
Figure 6: Inter-firm Movement Results in Higher Base Compensation



Source: Defendants' employee compensation data.

92. When the same comparison is made for total compensation, which includes stock compensation, overtime and bonus pay, the difference between compensation increases for movers and stayers is substantially larger, around 5 to 10 percent for the stayers and up to 45 percent for the movers. Some of the increase in total compensation during the first year of transition might be attributable to stock options and restricted stock granted to new hires as a sign-up incentive.

Figure 7: Inter-firm Movement Results in Higher Total Compensation



Source: Defendants' employee compensation data; SEC filings.

93. This analysis is common evidence capable of showing that price discovery has an effect on compensation of Defendants' employees, and thus that agreements restricting recruiting of Defendant employees would tend to suppress compensation.

4. Common Evidence Confirms that the Non-Compete Agreements Coincided with Periods of Economic Expansion that Otherwise Would Have Increased Compensation to Class Members

94. Common evidence can also be used to demonstrate that the timing of the agreements coincided with periods of expansion that would otherwise have caused compensation of class members to rise.

95. Cold-Calling is likely to be most active during the industry expansions in which the industry overall is enjoying rapid growth and facing supply constraints of workers at every level of experience.

96. During much of the class period, the Defendants collectively were experiencing a phase of rapid economic expansion and exhibited strong financial performance. Google grew from a startup with just eight employees in 1999 to a publicly traded company with over 30,000 employees in 2012. Apple tripled its revenue between 2005 and 2010 with widespread success of its consumer electronic products including the iPhone, iPod Touch and iPad. Adobe generated about $980 million in owner earnings in 2007, up from $580 million and $540 million in 2006 and 2005, respectively.[118] Between 1998 and 2011, Pixar released 11 blockbuster feature films resulting in more than $6 billion at the worldwide box office.[119]

- 'It's surreal in the Valley, compared to the rest of the country,' said Harj Taggar, a partner at startup incubator Y Combinator [in 2011]. 'It's so hard to hire people here – and salaries for engineers are going through the roof.'[120]

97. Equity distributions are especially important for retaining critical employees during expansions when many firms are actively recruiting talent. The normal vesting periods of three or four years align compensation with stock market performance, and create a loss for workers who leave. This makes them share in the loss of firm-specific knowledge assets that their departure creates. Equity grants and profit-sharing are used to promote employee loyalty and retain firm-specific knowledge assets,[121] as that term is understood in economic literature.

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[118] Ponzio, Joe, "With Adobe, Growth and Value are Joined at the Hip," Seeking Alpha, February 4, 2008, http://seekingalpha.com/article/62919-with-adobe-growth-and-value-are-joined-at-the-hip.

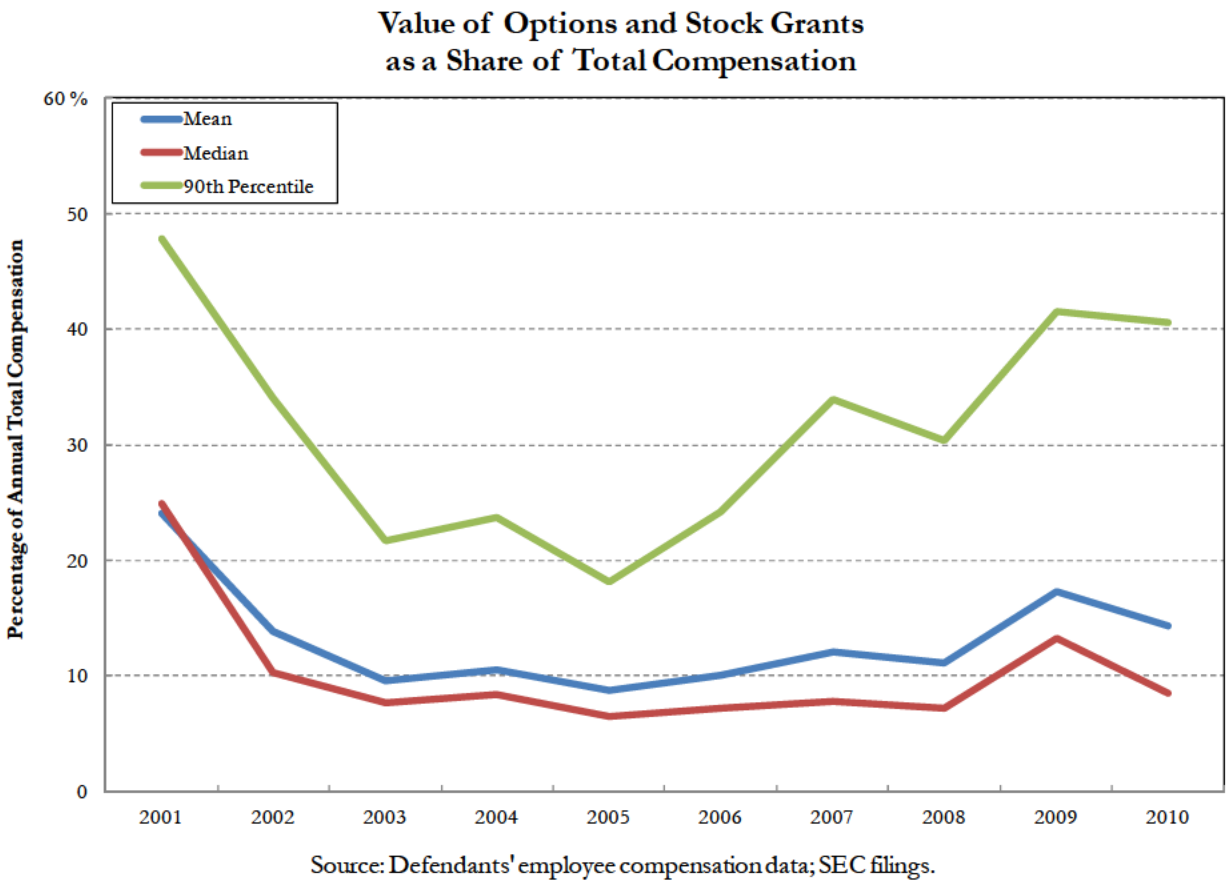
[119] Pixar, "Corporate Overview," http://www.pixar.com/companyinfo/about_us/overview.htm [Accessed 04/06/2012].

[120] Wagner, Alex, "As National Employment Stalls, Job Market Booms In Silicon Valley," Huffington Post, July 8, 2011.

[121] See e.g., Grant, R. M., "Toward a Knowledge-Based Theory of the Firm," *Strategic Management Journal*, 17

98. Figure 8 below illustrates the equity share of total compensation from 2001 to 2011. The median (across all employees at all firms), the mean and the 90th percentile are all depicted. The share of compensation in the form of equity declined very significantly during the economic downturn from 2001 to 2003. When the market started to improve in 2004, equity bumped up a little, but as it continued to improve in 2005 equity compensation fell, coincident with the initialization of the non-compete agreements. If we use 2010 and 2011 as the relevant "after" expansion period, the 90th percentile has about a 40 percent equity supplement compared with 20 percent in 2005, about 23 percent in 2006 and about 33 percent in 2007.

Figure 8: Use of Equity Compensation



Source: Defendants' employee compensation data; SEC filings.

(Winter Special Issue), 1996, pp. 109-122.

99. Revenues are required to support salary increases, and a surge in profits over time is likely to be spent partly on raising wages and retaining key employees. Figure 9 illustrates the growth in revenue per worker at Apple and the average total compensation per worker. Apple revenues per worker doubled from around $500,000 in 2001 around $1,000,000 in 2005, but [redacted] The Apple Non-Compete Agreements went into effect when Apple revenues surged, and when the risk of sharing the gains with the workforce was a threat to the firms' high levels of profits.

Figure 9: Growth of Apple's Revenue and Compensation

Apple's Revenue and Average Total Compensation Per Employee

Source: Defendants' employee compensation data; SEC Filings.

100. Following a period of industry weakness[122] in which the forces for increases in compensation were weak, normal market forces in 2005 and subsequently would have resulted in a distribution of some of that net revenue to the workforce. It is not surprising that the anti-Cold-Calling agreements were put in place in 2005 and subsequently, when employment and revenues began to grow substantially and when competition for critical workers was likely more intense. The agreements were formed when they were most likely to be effective and to matter.

B. Classwide Evidence is Capable of Showing that the Non-Compete Agreements Suppressed the Compensation of All or Nearly All Members of the All-Employee Class and Technical Employee Class

101. Common evidence can likewise be used to demonstrate that the artificial suppression of employee compensation would have been widespread, extending to all or nearly all members of the All-Employee Class and Technical Employee Class. This Class-wide evidence includes all of the evidence set forth above capable of showing the link between the Non-Compete Agreements and suppressed compensation plus three additional categories of evidence: (a) economic theory implicating firm incentives to maintain worker loyalty by adhering to principles of internal equity through a rigid salary structure; (b) Defendants' documents reflecting their recognition and implementation of internal equity principles and more specifically demonstrating the broad effects on compensation of the Non-Compete Agreements; and (c) multiple regression analyses capable of showing both that compensation of All-Employee Class and Technical Employee Class members is governed largely by common factors and that Defendants maintained rigid salary structures such that one would expect Non-Compete Agreements to have widespread effects on compensation of All-Employee Class and Technical Employee Class members.

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[122] Luo, Tian and Mann, Amar, "Crash and Reboot: Silicon Valley high-tech employment and wages, 2000-08," Monthly Labor Review, January 2010, p.61-65 and NOVA Workforce Board, "Silicon Valley in Transition," July 2011.

102. One key economic framework (introduced above) is built on the concept of firms' incentives to maintain and promote worker loyalty. Although economists often refer to the labor "market," most labor services are mediated not by commodity markets but by committed long-term relationships built on trust and understanding and mutual interests. If it were literally a commodity market the compensation paid to any particular employee would have to be both the highest that the employee could find and also the lowest that the employer could find at any particular point in time. If workers were commodities, every small change to external or internal conditions would lead to recontracting, separation, or termination. This would create enormous uncertainty and disruption and insecurity for employer and employee. Both sides of the bargain thus seek ways to turn the market transaction into a long-term relationship. A secure long-term relationship can come either from commitment (emotional or financial) to the mission of the organization, or from jointly owned firm-specific assets.[123]

103. Firms attempt to create loyalty by getting buy-in to the firm's mission and by making the place of work as appealing as possible.[124] If these intangibles are insufficient, firms also have employee stock options (ESOPs) that give employees a stake in their firm.[125]

104. One foundation of employee loyalty is a feeling of fairness that can translate into a sharing of the rewards with more equality than a market might otherwise produce. "Equitable" compensation practices spread wage increases or reductions across broad categories of workers.[126] This implies that when

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[123] Becker, Gary, "Nobel Lecture: The Economic Way of Looking at Behavior," *The Journal of Political Economy*, Vol. 101, No.3 (June 1993), pp. 385-409.

[124] See GOOG-HIGH TECH-00038364-395 at 368-369.

[125] Oyer, Paul and Schaefer, Scott, "Why Do Some Firms Give Stock Options To All Employees?: An Empirical Examination of Alternative Theories," March 26, 2003.

[126] See e.g., Rees (1993) who describes the role of demand and the impact of market forces on salary structures of university faculty. (Rees, A. "The Role of Fairness in Wage Determination," *Journal of Labor Economics,* 1993, Vol. 11, No. 1, pt. 1.) See also, Mas, "Pay, Reference Points, and Police Performance," *The Quarterly Journal of Economics*, August 2006.

outside opportunities put pressure at one point in the wage structure calling for higher wages for a few, firms tend to maintain the overall firm wage structure, rewarding everyone for the improved outside opportunities of some workers.[127]

105. To maintain loyalty, it is usually better for a firm to anticipate rather than to react to outside opportunities, since if a worker were to move to another firm at a much higher level of compensation, coworkers left behind might feel they have not been fairly compensated. That can have an adverse effect on worker loyalty, reducing productivity and increasing interest in employment elsewhere. To avoid this reduction in loyalty in the face of competition, firms may make preemptive improvements in their compensation packages.[128]

106. As discussed throughout this Report, Class-wide evidence is capable of showing that Cold-Calling--as well as just the threat of Cold-Calling--puts upward pressure on compensation. Economic theory describes factors that drive firms, like the Defendants, toward equitable pay practices that would be expected to spread the impact of an agreement to suppress Cold-Calling across all or almost all workers in a firm. Non-compete agreements allow firms to be more relaxed in maintaining competitive compensation packages because such agreements 1) suppress competition directly; 2) reduce the risk of employees becoming aware of pay practices elsewhere; and 3) otherwise eliminate competition for "passive" employees.

[127] Concerns about fairness are observed within the defendants and in public discussions relating to salaries at firms like the defendants. See e.g., 76512DOC000638-677 at 644 and 656-658 ("Use benchmark salary surveys to create criteria on which to evaluate jobs across Intel… supports consistence and equity within and across business groups."). See also, ADOBE_008047-049 at 047 and GOOG-HIGH-TECH-00193377-382 at 380-381.

[128] See e.g., GOOG-HIGH-TECH-00194945 –946.

1. *Defendants' Internal Documents Constitute an Additional Form of Common Proof Capable of Showing that the Non-Compete Agreements Suppressed Compensation to All or Nearly All Members of the All-Employee Class and Technical Employee Class*

107. Documents reflecting Facebook's aggressive efforts to recruit through Cold-Calling employees from Google in 2010 provide a particularly interesting example of the impact Cold-Calling can have on compensation firm-wide. Google recognized that it had become the target of substantial recruiting from Facebook.[129] In some cases other Google employees, who apparently had not received such offers, used leaked information about Google's counter offers in their own negotiations with Google.[130] Google recognized the threat this posed to its employee relationships.[131] Google's efforts to counter this threat included compensation benefits to employees of whom Google learned were being recruited as well as a firm wide increase in compensation of 10 percent (plus an immediate $1,000 bonus to all employees).[132] Other firms, including Intuit, Intel, and Adobe recognized what was driving this increase.[133]

108. Like Google and Apple during the conspiracy period,[134] Facebook was a premier destination for high-tech employees, and Facebook hired at a rapid pace. Between 2005 and 2011, Facebook expanded its employees by up to 50 percent every year, hiring 1,073 employees between 2010 and 2011.[135] In order

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[129] "Our research indicates that Google continues to be one of the top organizations [redacted] GOOG-HIGH-TECH-00193360-367 at 360.

[130] See GOOG-HIGH-TECH-00193435-446 at 437.

[131] GOOG-HIGH-TECH-00193217-224 at 217.

[132] See GOOG-HIGH-TECH-00193377-382 at 380. See also, GOOG-HIGH-TECH-00193406-411, GOOG-HIGH-TECH-00193360-367, and GOOG-HIGH-TECH-00193217-224.

[133] See, e.g., INTUIT_016652, 76633DOC000369 (Intel), and ADOBE_025894.

[134] Google's global headcount went from approximately 3,000 employees prior to the start of the conspiracy to almost 20,000 by the end of 2009. Apple went from approximately 12,500 employees prior to the start of the conspiracy to approximately 37,000 by the end of 2009, as reported in 10-k filings.

[135] See GOOG-HIGH-TECH-00054804-806 at 805. [redacted]

to accomplish this (to "grow rapidly . . . at the rate they desire[d]"),[136] Facebook solicited employees of Google.[137] Google followed these recruiting efforts closely at the highest levels, including discussing them with Bill Campbell.[138]

109. [redacted]."[141]

110. The next month (and approximately two months after the DOJ's antitrust investigation was made public), Google announced it would increase the base salary of all of its salaried employees by 10% and provide an immediate cash

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[redacted]

[136] See PIX00000227.

[137] Facebook is estimated to have hired about 137 employees from Google by November 2010 Amir Efrati and Pui-Wing Tam "Google Battles to Keep Talent" Wall Street Journal, November 11, 2010, http://online.wsj.com/article/SB10001424052748704804504575606871487743724.html

[138] INTUIT_000013-018 at 013-015 (Jonathan Rosenberg forwarded an email to Bill Campbell in which Laszlo Bock, Google's Senior Vice President for "People Operations" described the "increased Facebook activity in the last 3 months versus the beginning of the year. They do seem to have gotten more serious once more about coming after Googlers.").

[139] GOOG-HIGH-TECH-00193360-367 at 361 ([redacted]).

[140] See GOOG-HIGH-TECH-00193360 - 367 at 364.

[141] See GOOG-HIGH-TECH-00193360 - 367 at 364.

bonus of $1,000 for every salaried employee.[142] Google referred to this project as the "Big Bang," and discussed it extensively beforehand with Intuit's Bill Campbell and Intel's Paul Otellini.[143] These discussions provide a powerful illustration of the common impact of Defendants' Agreements.

111. On October 8, 2010, Jonathan Rosenberg emailed Google's senior executives (and Bill Campbell) summarizing concerns from the "broader population" at Google regarding Google's counteroffer strategy. Employees who heard about other "Googlers" receiving counteroffers were upset: "It's impossible to keep something like this a secret. The people getting counter offers talk, not just to Googlers and Ex-Googlers, but also to the competitors where they received their offers (in the hopes of improving them), and those competitors talk too, using it as a tool to recruit more Googlers."[144] "And for the time that the person remains, there will be serious resentment among his/her peers for what seems like an unfair jump."[145]

112. This is an illustration of all three frameworks: (1) Price Discovery; (2) Equity and Loyalty; and (3) Firm-Specific Assets.

113. First, when employees discover information regarding their labor's value by receiving an offer from a competing employer, those employees use that information to negotiate higher salaries at their current employer, and so on, in an iterative process.

114. Second, those individuals tell others at their employer, who then "resent[]" the perceived "unfair jump" in pay, increasing pressure to match compensation

[142] GOOG-HIGH-TECH-00193377-382 at 380.

[143] See GOOG-HIGH-TECH-00195005 – 007, GOOG-HIGH-TECH-00196108, GOOG-HIGH-TECH-00196687, GOOG-HIGH-TECH-00196689, and GOOG-HIGH-TECH-00194945 –946.

[144] INTUIT_039098-100 at 098.

[145] INTUIT_039098-100 at 098. See also, GOOG-HIGH-TECH-00194721-722.

increases broadly.[146] This is often experienced in emotional terms: "it feels like my loyalty is being punished."[147]

115. Third, [redacted][148]

116. Alan Eustace, a Senior VP of Google, confirmed these frameworks in the same document (again, in an email also sent to Bill Campbell): "every time an employee has a better offer, a company is forced to decide how badly they want the employee, and what they are ultimately worth. . . . You can't afford to be a rich target for other companies."[149]

117. Eustace also explained why many employee candidates will not learn "what they are ultimately worth" without Cold-Calling by a competing company: actively seeking out such offers and using them to negotiate for higher compensation "is a high risk strategy" that "seriously questions your loyalty and character, which could have long-term consequences to your career that offset any financial gain."[150] The "right approach" to respond to such recruiting efforts by a labor market competitor "is to not deal with these situations as one-off's but have a systematic approach to compensation that makes it very difficult for anyone to get a better offer."[151]

118. Google's announcement did not escape the attention of other Defendants. First, the same executives at Intuit and Intel who entered into the Agreements

[146] See INTUIT_039098-100 at 099.

[147] INTUIT_039098-100 at 099.

[148] INTUIT_039098-100 at 099.

[149] INTUIT_039098-100 at 098.

[150] INTUIT_039098-100 at 098.

[151] INTUIT_039098-100 at 098.

with Google were sent them directly.[152] Other Defendants paid close attention as well.[153]

119. [redacted][155]

2. Econometric and Statistical Analysis of Defendants' Compensation Data Is Also Capable of Demonstrating That the Compensation Suppressing Effects of the Non-Compete Agreements Would Be Broadly Experienced By Members of the All-Employee Class and Technical Employee Class

120. A firm's commitment to principles of "internal equity" is evidenced by the imposition and maintenance of a somewhat rigid salary structure. What that means is that Cold-Calling and related practices would be expected to increase compensation across the board rather than be narrowly focused on the skills that are most in demand at any point in time.[156] As a result, analysis of the application of standard economic labor theory to this case constitutes common evidence bolstering Plaintiffs' proof that the Non-Compete Agreements would broadly affect members of the All-Employee Class and Technical Employee Class. Moreover, economic analysis of Defendants' salary structures and compensation data reveal that each Defendant had a rigid salary structure,

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[152] See, e.g., INTUIT_039098. (Campbell); 76616DOC005974 and "Google,Board of Directors," http://investor.google.com/corporate/board-of-directors.html (Paul Otellini at Intel, who was a Google Board Member throughout the conspiracy period).

[153] See, e.g., ADOBE_025894-898 at 898 (internal discussion in which Adobe considers whether its employees will want a raise similar to the one Google announced).

[154]See GOOG-HIGH TECH-00193377-382.

[155] See GOOG-HIGH-TECH-00193406-411 at 406 [redacted].").

[156] See eg. GOOG-HIGH TECH-00042588-640 at 633 (Talking about the equity program, "In special cases and with VP approval, we can exceed target if supported by sound business rationale. In practice, we rarely deviate from the guidelines given our philosophy around internal equity.").

where compensation of employees within specific positions and within each company tended to move together over time through the relevant periods.

121. The Class-wide evidence I have reviewed and analyzed shows that Defendants had highly structured compensation systems built on a two dimensional matrix with several grades and many titles. In many firms, compensation is first and foremost linked to the grades, each of which encompasses diverse kinds of activities which nonetheless receive roughly the same level of compensation.[157] For example, Defendants Adobe, Apple, Google, Intel, and Intuit used grades explicitly and Defendants Pixar and Lucasfilm may have done so as well (though their data in this regard was unclear at the time of this Report). The titles identify specific activities and defined career paths, as in Software Engineer Step 1, Software Engineer Step 2, and so on.

122. Typically, high level management established ranges of salaries for grades and titles which left relatively little scope for individual variation.[158] Defendants established and regularly updated compensation levels with the following aims:

a. Providing similar compensation for all employees in the same employment category,[159]

b. Providing specific relative compensation levels for employees in different, hierarchically ordered, employment categories, or "salary grades,"[160]

c. Retaining employees,[161] and

d. Maintaining employee productivity and contentment.

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[157] See e.g., 76512DOC000638-677 at 643 and 656-660.

[158] See e.g., 76512DOC000638-677 at 644 ("Use benchmark salary surveys to create criteria on which to evaluate jobs across Intel") and GOOG-HIGH TECH-00042588-640 at 612 and 632.

[159] PIX00006026-6036 at 034 and GOOG-HIGH TECH-00042588-640 at 643.

[160] See e.g., 76512DOC000638-677 at 671 ("[redacted]"). See also, GOOG-HIGH TECH-00028981- 9027 at 9007.

[161] GOOG-HIGH-TECH-00036781-839 at 785.

123. An Intel compensation document indicates its policies were aimed toward maintaining a salary structure that is consistent with internal equity.[162] In a page entitled "Internal Equity & Performances Expectations," in order to preserve "internal equity," managers are to answer three questions when slotting a job applicant within the current employees in the group: "How do backgrounds compare?", "How do expertise and skill compare?," and "Where would the manager rank this person within their department based on their expectation of the applicant's contribution and job performance?" Each employee, whether "technical" or "administrative," is assigned a "grade" primarily according to his/her education and experience. His/her base pay was then set within the "grade level." The range of pay within each level was relatively narrow.[163]

124. An internal Pixar email discussed an across-the-board adjustment for "our under paid engineers." "We want to send a clear message to these engineers that we value them at least as much as some new hires who are seeing much more competitive offers from other companies." The email refers to using a "leveling matrix" to "give us a consistent framework for evaluating the expected contribution of our software engineers."[164]

125. Google also has policies to ensure that new hires' salaries are positioned correctly relative to others in the firm. When determining base pay for new candidates, Google takes into consideration internal equity along with market data, candidate grade, current compensation, and competing offers.[165] Additional evidence of compensation equity at work is Google's response to

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[162] See 76512DOC000638-677 at 658 ("Offer Development Overview").

[163] See 76579DOC002323 pp. 1-37.

[164] PIX00049648-650 at 648. See also ADOBE_019192 (Internal email on meeting with Adobe CEO re: establishing "salary matrices." "We need to recommend the matrix . . . that will provide market competitive base salary adjustments"), GOOG-HIGH TECH-00036716-780 at 729-730 (Presentation on "Google Compensation Basics" includes section on "job leveling" and "benchmarking"), and 231APPLE009282-283 ([redacted]).

[165] GOOG-HIGH TECH-00038364-395 at 373, GOOG-HIGH TECH-00037936-973 at 963 and GOOG-HIGH TECH-00042588-640 at 614.

loss of employees to Facebook (described above). The ten percent increase in base salary *across the board* was said to "attract new recruits and preempt defections."[166]

> "Reporting from San Francisco — Google Inc.'s decision to give all of its 23,300 employees a 10% pay raise next year — and a $1,000 bonus to boot — is just the latest volley in what has become a full-fledged war for top Silicon Valley talent."[167]

126. All Defendants offered stock grants or options, and/or bonuses. While inequity in this form of compensation could offset pay equity in base compensation, stock options and bonuses may be calculated formulaically based on individual and company performance in a way that maintains an equitable total compensation structure.[168] Indeed, stocks or bonuses were granted to the majority of employees at all of the Defendants. As shown in Figure 10, 93 percent of the employee-year[169] compensation records included these salary supplements.

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[166] Amir Efrati and Pui-Wing Tam "Google Battles to Keep Talent" Wall Street Journal, November 11, 2010, http://online.wsj.com/article/SB10001424052748704804504575606871487743724.html

[167] Guynn, Jessica, "War heats up for top Silicon Valley talent," Los Angeles Times, November 10, 2010.

[168] See e.g., 76512DOC000638-677 at 668 ("Option run rates typically non-negotiable"). See also, 76512DOC000638-677 at 644, and 656-667.

[169] An employee employed in December of a particular year. An employee of a firm for five years (each of which he was present for December), would have five employee-years.

Figure 10: Use of Supplemental Compensation was Widespread

Fraction of Employee-years with Bonus or Equity Grants

Employer	Mean	Number of Observations
(1)	(2)	(3)
Adobe	0.84	50,862
Apple	[redacted]	[redacted]
Google		
Intel		
Intuit	0.88	63,700
Lucasfilm	0.51	9,118
Pixar	0.74	12,654
All	0.93	985,428

Source: Defendants' employee compensation data.

127. Evidence of the structure of compensation in each of ten years from 2001 to 2011 is reported in the ten regression equations in Figure 11 below.

128. Each equation explains the total compensation inclusive of stock grants of each salaried employee in terms of a number of basic observable employee characteristics such as age, number of months in the company, gender, location, title, and employer.[170] What these analyses show is that about 90 percent of the variability in a class member's compensation can be explained by these variables.[171] This and the additional fact that the coefficients in these regressions vary slowly over time (meaning the role played by these factors is

[170] These types of regressions can be found in many academic studies of wage structure. See e.g., Menezes-Filho, N. A., Muendler, M., and Garey Ramney. "The Structure of Worker Compensation in Brazil, With A Comparison To France And The United States." *The Review of Economics and Statistics*, May 2008, 90(2): 324-346.

[171] Other variables that would have been known to the employee and employer but where not available at all or for large numbers of employees in the data (such as education) would likely explain substantially more of the variation.

relatively stable), are symptoms of firmwide compensation structures, and the formulaic way in which total compensation was varied over time.

Figure 11: Common Factors Identify a Firmwide Compensation Structure

Hedonic Regressions Of Wage Structure
All-Salaried Employee Class

Observation: Employee ID record in December of each year
Dependant Variable: Log(Total Annual Compensation)

	Dec-01			Dec-02			Dec-03			Dec-04		
Variable	Estimate	St. Error	T-Value	Estimate	St. Error	T-Value	Estimate	St. Error	T-Value	Estimate	St. Error	T-Value
Log(Age) (Years)	0.72	0.08	9.60	1.03	0.08	13.26	0.74	0.08	9.29	1.23	0.08	15.16
Log(Age)^2	-0.10	0.01	-9.66	-0.14	0.01	-13.06	-0.09	0.01	-8.62	-0.16	0.01	-14.38
Log(Company Tenure) (Months)	-0.07	0.00	-17.28	-0.12	0.00	-29.45	-0.02	0.00	-4.88	0.01	0.00	4.99
Log(Company Tenure)^2	0.00	0.00	9.38	0.01	0.00	20.40	0.00	0.00	1.70	0.00	0.00	-6.04
Male	0.00	0.00	1.15	0.01	0.00	3.60	0.01	0.00	4.49	0.01	0.00	6.81
Employer Indicators	YES			YES			YES			YES		
Location (State Indicators)	YES			YES			YES			YES		
Title Indicators	YES			YES			YES			YES		
Constant	YES			YES			YES			YES		
Observation	64,264			61,768			60,764			62,645		
R-square	**0.95**			**0.94**			**0.94**			**0.93**		

	Dec-05			Dec-06			Dec-07			Dec-08		
	Estimate	St. Error	T-Value	Estimate	St. Error	T-Value	Estimate	St. Error	T-Value	Estimate	St. Error	T-Value
Log(Age) (Years)	0.77	0.08	9.93	0.96	0.09	11.28	1.25	0.10	12.71	1.13	0.09	13.06
Log(Age)^2	-0.09	0.01	-8.74	-0.12	0.01	-10.69	-0.17	0.01	-12.53	-0.15	0.01	-12.59
Log(Company Tenure) (Months)	0.08	0.00	38.46	-0.03	0.00	-9.31	-0.03	0.00	-9.55	0.02	0.00	6.84
Log(Company Tenure)^2	-0.01	0.00	-27.73	0.01	0.00	13.28	0.00	0.00	9.36	0.00	0.00	-3.89
Male	0.01	0.00	9.18	0.02	0.00	9.57	0.01	0.00	4.97	0.01	0.00	8.73
Employer Indicators	YES			YES			YES			YES		
Location (State Indicators)	YES			YES			YES			YES		
Title Indicators	YES			YES			YES			YES		
Constant	YES			YES			YES			YES		
Observation	71,768			72,380			71,804			73,897		
R-square	**0.928**			**0.923**			**0.909**			**0.916**		

	Dec-09			Dec-10			Dec-11		
	Estimate	St. Error	T-Value	Estimate	St. Error	T-Value	Estimate	St. Error	T-Value
Log(Age) (Years)	1.10	0.09	11.54	0.95	0.10	9.57	0.97	0.08	11.54
Log(Age)^2	-0.15	0.01	-11.59	-0.12	0.01	-9.29	-0.13	0.01	-11.19
Log(Company Tenure) (Months)	0.04	0.00	9.35	0.02	0.00	6.33	0.05	0.00	17.99
Log(Company Tenure)^2	0.00	0.00	-3.14	0.00	0.00	-3.29	0.00	0.00	-7.39
Male	0.01	0.00	7.59	0.02	0.00	8.17	0.01	0.00	8.79
Employer Indicators	YES			YES			YES		
Location (State Indicators)	YES			YES			YES		
Title Indicators	YES			YES			YES		
Constant	YES			YES			YES		
Observation	73,722			78,673			88,431		
R-square	**0.922**			**0.898**			**0.918**		

Note: (1) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, value of equity compensation granted.
(2) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.

Source: Defendants' employee compensation data; SEC Filings.

129. The regressions reported in the figure above are based on data from all defendants and presume that each defendant had a similar internal compensation system although the "employer effect" allows compensation to differ by a fixed percent across firms. Figure 12 shows a summary of the R-squared statistic for hedonic regressions performed separately for each defendant and year. The R-squared statistic measures the percentage of the variability in compensation that is explained by the variables in the model. The majority of the R-squared statistics are around 90 percent demonstrating that almost the entire variation in salaries within each firm at each point in time can be explained by a common set of employee characteristics.

130. The fact that nearly all variability in class member compensation at any point in time can be explained by common variables means there was a systematic structure to employee compensation at each of the Defendant firms. As a result, one would expect that significant exogenous factors like the imposition of Non-Compete Agreements would be expected to have effects that would be felt across a broad swathe of employees. Furthermore, the fact that the coefficients in my regressions did not vary substantially over time suggests that compensation structures were relatively stable over time. The systematic structure and the formulaic way in which compensation changed over time is consistent with internal equity considerations as discussed in the economic literature. In other words, my regression analyses are capable of showing that the compensation of class members tended to move together over time and in response to common factors. Accordingly, this evidence, along with my other analysis of the economics of Defendants' compensation, is capable of showing that the effects on compensation from the Non-Compete Agreements would be expected to be broadly experienced by all or nearly all members of the All-Employee Class and Technical Employee Class.

Figure 12: Common Factors Explain Within-Firm Compensation Structure

Summary of R-squared From Yearly Hedonic Regressions By Defendant
All-Salaried Employee Class

Observation: Employee ID record in December of each year
Dependant Variable: Log(Total Annual Compensation)

Year	ADOBE	APPLE	GOOGLE	INTEL	INTUIT	PIXAR	LUCASFILM
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2001	0.91	0.89	0.93	0.96	0.88	-	-
2002	0.93	0.87	0.94	0.95	0.90	0.84	-
2003	0.92	0.91	0.79	0.96	0.90	0.71	-
2004	0.94	0.91	0.89	0.96	0.89	0.85	-
2005	0.87	0.91	0.80	0.97	0.89	0.83	-
2006	0.94	0.89	0.79	0.97	0.89	0.90	0.88
2007	0.92	0.87	0.75	0.96	0.88	0.92	0.87
2008	0.93	0.87	0.80	0.97	0.88	0.93	0.92
2009	0.88	0.87	0.86	0.96	0.88	0.94	0.94
2010	0.91	0.86	0.77	0.96	0.88	0.93	0.94
2011	0.93	0.86	0.83	0.97	0.88	0.95	0.94

Note: Hedonic regressions performed separately for each defendant and year by using log(Total annual compensation) as a dependant variable and the following independent variables: log(age), log(age)^2, log(company tenure), log(company tenure)^2, male indicator, location indicators, and title indicators. Pixar's R-squared in 2001 is missing due to insufficient observations. Regressions for Lucasfilm were not performed for 2001-2005 due to absence of employee titles in the data.

Source: Defendants' employee compensation data; SEC Filings.

131. The Technical Employee Class also has a compensation structure that is captured by the regression equations reported in Figure 13 that apply to employees at all firms and also R-squared statistics for the regressions defendant by defendant as reported in Figure 14.

Figure 13: Common Factors Identify a Firmwide Compensation Structure

Hedonic Regressions Of Wage Structure
Technical, Creative, and R&D Class

Observation: Employee ID record in December of each year
Dependant Variable: Log(Total Annual Compensation)

	Dec-01			Dec-02			Dec-03			Dec-04		
Variable	Estimate	St. Error	T-Value	Estimate	St. Error	T-Value	Estimate	St. Error	T-Value	Estimate	St. Error	T-Value
Log(Age) (Years)	0.41	0.12	3.40	0.95	0.12	7.96	0.70	0.12	5.94	1.28	0.12	10.62
Log(Age)^2	-0.06	0.02	-3.84	-0.13	0.02	-8.19	-0.09	0.02	-5.70	-0.17	0.02	-10.24
Log(Company Tenure) (Months)	-0.07	0.01	-13.28	-0.13	0.01	-23.33	0.01	0.00	2.69	0.04	0.00	10.75
Log(Company Tenure)^2	0.00	0.00	6.38	0.01	0.00	15.50	0.00	0.00	-5.57	-0.01	0.00	-12.58
Male	0.00	0.00	1.46	0.01	0.00	2.32	0.00	0.00	1.54	0.01	0.00	4.23
Employer Indicators	YES			YES			YES			YES		
Location (State Indicators)	YES			YES			YES			YES		
Title Indicators	YES			YES			YES			YES		
Constant	YES			YES			YES			YES		
Observation	33,993			33,431			33,072			32,999		
R-square	**0.89**			**0.89**			**0.88**			**0.88**		

	Dec-05			Dec-06			Dec-07			Dec-08		
	Estimate	St. Error	T-Value	Estimate	St. Error	T-Value	Estimate	St. Error	T-Value	Estimate	St. Error	T-Value
Log(Age) (Years)	0.62	0.11	5.57	0.95	0.12	8.16	1.47	0.13	10.89	1.34	0.11	11.86
Log(Age)^2	-0.07	0.02	-4.84	-0.13	0.02	-7.88	-0.20	0.02	-11.02	-0.18	0.02	-11.65
Log(Company Tenure) (Months)	0.10	0.00	33.58	-0.03	0.00	-6.07	-0.03	0.00	-6.12	0.04	0.00	9.42
Log(Company Tenure)^2	-0.01	0.00	-26.68	0.00	0.00	7.72	0.00	0.00	5.52	0.00	0.00	-6.98
Male	0.01	0.00	5.33	0.02	0.00	7.93	0.01	0.00	3.05	0.02	0.00	7.24
Employer Indicators	YES			YES			YES			YES		
Location (State Indicators)	YES			YES			YES			YES		
Title Indicators	YES			YES			YES			YES		
Constant	YES			YES			YES			YES		
Observation	39,736			40,458			41,862			43,643		
R-square	**0.879**			**0.870**			**0.848**			**0.859**		

	Dec-09			Dec-10			Dec-11		
	Estimate	St. Error	T-Value	Estimate	St. Error	T-Value	Estimate	St. Error	T-Value
Log(Age) (Years)	1.28	0.12	10.56	1.08	0.13	8.45	1.03	0.11	9.79
Log(Age)^2	-0.18	0.02	-10.84	-0.15	0.02	-8.45	-0.14	0.01	-9.69
Log(Company Tenure) (Months)	0.04	0.00	8.83	0.02	0.00	4.98	0.05	0.00	13.42
Log(Company Tenure)^2	0.00	0.00	-3.39	0.00	0.00	-2.31	0.00	0.00	-5.61
Male	0.02	0.00	6.50	0.02	0.00	7.21	0.02	0.00	7.89
Employer Indicators	YES			YES			YES		
Location (State Indicators)	YES			YES			YES		
Title Indicators	YES			YES			YES		
Constant	YES			YES			YES		
Observation	44,839			48,401			54,695		
R-square	**0.885**			**0.841**			**0.878**		

Note: (1) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, value of equity compensation granted.
(2) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.

Source: Defendants' employee compensation data; SEC Filings.

Figure 14: Common Factors Explain Within-Firm Compensation Structure

Summary of R-squared From Yearly Hedonic Regressions By Defendant Technical, Creative, and R&D Class

Observation: Employee ID record in December of each year
Dependant Variable: Log(Total Annual Compensation)

Year	ADOBE	APPLE	GOOGLE	INTEL	INTUIT	PIXAR	LUCASFILM
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2001	0.86	0.83	0.79	0.92	0.78	-	-
2002	0.91	0.84	0.87	0.90	0.84	0.64	-
2003	0.89	0.87	0.66	0.91	0.86	0.52	-
2004	0.92	0.87	0.83	0.90	0.85	0.67	-
2005	0.89	0.87	0.62	0.94	0.86	0.65	-
2006	0.92	0.84	0.68	0.93	0.85	0.75	0.86
2007	0.88	0.81	0.66	0.93	0.82	0.83	0.83
2008	0.90	0.81	0.68	0.94	0.85	0.86	0.90
2009	0.86	0.80	0.81	0.93	0.86	0.86	0.92
2010	0.87	0.79	0.68	0.94	0.85	0.87	0.92
2011	0.91	0.76	0.76	0.95	0.84	0.87	0.93

Note: Hedonic regressions performed separately for each defendant and year by using log(Total annual compensation) as a dependant variable and the following independent variables: log(age), log(age)^2, log(company tenure), log(company tenure)^2, male indicator, location indicators, and title indicators. Pixar's R-squared in 2001 is missing due to insufficient observations. Regressions for Lucasfilm were not performed for 2001-2005 due to absence of employee titles in the data.

Source: Defendants' employee compensation data; SEC Filings.

132. The compensation structure around a common baseline can also be seen by looking at compensation trends of some of the major titles at Defendants. These data use the regressions reported in Figure 12 to control for changes within each title in age, tenure, and location. We refer to these as "constant attribute" compensation.

Figure 15: Constant Attribute Compensation of Major Apple Job Titles

Base Salary

Source: Defendants' employee compensation data.

Total Compensation

Source: Defendants' employee compensation data; SEC filings.

Figure 16: Constant Attribute Compensation of Major Google Job Titles

Base Salary

Source: Defendants' employee compensation data.

Total Compensation

Source: Defendants' employee compensation data; SEC filings.

133. To illustrate this further, Figure 17 depicts salary trends of top titles for Apple. Each line represents a single year. The collection of lines indicates that, [redacted]

Figure 17: Constant Attribute Compensation Ranking of Major Apple Job Titles is Generally Stable

Source: Defendants' employee compensation data; SEC filings

134. These charts reveal a persistent salary structure across employees consistent with important elements of equity in the Defendants' compensation practices. The non-compete-agreements which might tend to focus on subsets of workers would nonetheless have effects that would spread across all or almost all employees at the firm in order to maintain the overall salary structure.

3. *Standard Econometric Analysis Is Capable of Showing That the Non-Compete Agreements Artificially Suppressed Compensation to the Members of Each Class Generally*

135. I have concluded that standard forms of econometric analysis are capable of computing the aggregate amount of compensation suppression to the All-Employee Class and Technical Employee Class caused by the Non-Compete Agreements.

136. An estimate of the effect of the Non-Compete Agreements on employee compensation can be found by contrasting compensation during the periods when the Agreements were in effect with compensation before and after the Non-Compete Agreements.

137. A search for comparison periods needs to be sensitive to the economic cycle. The interval of time for which all the Defendants have produced compensation data extends from 2001 to 2011. This ten-year interval includes a mild U.S. recession, a severe global recession, two tepid U.S. recoveries and a brief period of housing-led high growth. Roughly speaking, we can divide the 2001 to 2011 period as shown in Figure 18.

Figure 18: Growth Cycle Periods for the U.S. Economy

Period	Growth
(1)	(2)
2001	Mild US recession
2002 - 2003	Tepid recovery
2004 - 2005	Housing led growth
2006 - 2007	Weakening growth from weakening housing
2008 - 2009	Severe global recession
2010 - 2011	Tepid recovery

138. Figure 19 reports the average percent change by year in total compensation for all seven Defendants.[172] Total compensation is the sum of December base

[172] In addition to the mean, the table includes the median, the 90th percentile, the standard deviation and the number of observations.

salary bonuses, overtime and equity compensation. Observations are restricted to cases in which there was no change in employer.

139. The year 2002 in the wake of the 2001 recession has a large 4.7 percent decline in average total compensation and that was followed by another 2.3 percent decline in 2003. Circumstances for employees improved dramatically in 2004 with an average 10.3 percent increase in total compensation. Next comes the out-of-place small 0.5 percent increase in 2005, coincident with the start of the Non-Compete Agreements. Subsequently the average gains in compensation fluctuated between 6 percent and 9 percent, with the value of 6.8 percent in 2008 in the midst of the severe global recession.

Figure 19: Average Percent Change in Total Compensation

		Change in Total Compensation				Estimated Underpayment	
Year	Number of Employees	Mean	Median	90th Percentile	Std. Dev.	Initial[1]	Cumulative
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2002	58,465	(4.7)%	(1.5)%	10.2 %	19.5 %		
2003	58,176	(2.3)	(0.0)	13.2	19.9		
2004	57,835	10.3	11.5	22.9	18.7		
2005	59,494	0.5	0.2	14.7	20.3	(9.5)%	(9.5)%
2006	64,620	9.1	8.8	24.7	23.3	(0.9)	(10.3)
2007	64,680	7.4	4.3	26.8	26.0	(2.6)	(12.9)
2008	66,055	6.8	8.9	23.1	25.7	0.0	(12.9)
2009	69,178	7.4	2.8	34.9	24.4	0.0	(12.9)
2010	69,727	6.5	8.0	22.9	22.7		
2011	74,989	9.7	7.6	29.4	23.5		
Average		**5.1 %**	**5.1 %**	**22.3 %**	**22.4 %**		

[1] Calculated as the average change in total compensation for the year minus the average changes in total compensation in 2004 and 2011.

Notes: (1) Change in compensation measured only on employees that did not switch jobs from previous year
(2) Total compensation measured as base salary as of December plus annual bonuses, overtime compensation, and stock options and restricted stock awards.

Source: Defendants' employee compensation data; SEC filings.

140. Before undertaking a formal regression analysis of damages, we can use these annual numbers to do a preliminary informal impact assessment. The impact is suggested by comparing what was happening during the agreement period with

what was happening in relevant periods before and after. The years 2004 and 2011 arguably are useful before and after comparisons since these reveal the kind of compensation increases that occur in expansion periods that were similar to 2005-2007. The "during" years 2008 and 2009 were severe recession years for which there may be no relevant direct comparisons. The column labeled "Estimated Underpayment" has values in 2005-2007 equal to the difference between the percent increase in total compensation that actually occurred minus the average of total compensation in 2004 and 2011. This same column has zero values for 2008 and 2009, built on the idea that the weak economy would not have resulted in increases in those periods. The last column cumulates these effects to find the total impact year by year. A large impact on compensation comes in 2005 since that 0.5 percent actual change in average total compensation translates into a 9.5 percent undercompensation. The under-compensation cumulates to 12.9 percent in 2009.

141. While the results in Figure 19 are suggestive, they rely on informal choices of comparison period, and they do not make any distinctions among the defendants. Regression analysis is a better approach because it allows the choice of comparison period to be "constructed" statistically, and it allows for differences among defendants as well as for employees. Figure 20 reports a regression equation which explains the logarithm of total compensation at the individual level with a variety of individual, firm and temporal effects. The variables are defined in Figure 21 and the implied effects of the agreements on total compensation are recorded in Figure 22.

142. The variables in the regression in Figure 20 are divided by solid borders into five principle categories:

- Conduct Effects: How the Agreements affected total compensation and how the effects vary across time, firms and individuals,
- Persistence: How the effects linger over time,
- Worker Effects: How compensation normally varies across workers,
- Industry Effects: How compensation normally varies over time, and

- Employer Effects: How compensation normally varies across firms.

143. The worker variables are age, company tenure, and gender. The variables that drive the temporal changes are rate of growth of payroll jobs in information in Santa Clara County, the number of new employees hired by all defendants, the number of workers who moved between Defendants and a time trend. The effects that vary across employers are global revenue relative to the global workforce and the rate of growth thereof, the number of new workers hired relative to the previous year's workforce, and indicators that allow for distinct differences in compensation for each employer.

144. The persistence variables are the levels of total compensation in the previous year and the year before that, two for each employer. The fact that these numbers sum to around 90 percent indicates very persistent effects, meaning when a worker gets a bump up in compensation in some year that makes him or her better off than comparable coworkers, that effect lingers on for many years.

145. The CONDUCT variable measures the fraction of months in each year during which the employer was involved in one or more of the agreements. The conduct variable is interacted with three variables to allow for the possibility that the agreements had effects that varied over time, across firms and across individuals.

146. This regression model can be used to estimate the undercompensation year by year, employer by employer, reported in Figure 22. The part of the estimated regression that involves the CONDUCT variable is used to estimate the immediate impact of the illegal CONDUCT. These immediate impacts are propagated over time as implied by the dynamic structure of the model determined by the coefficients on the once-lagged and twice-lagged total compensation explanatory variables that follow the CONDUCT variables in the regression. The totals of the direct and secondary effects of the agreements on total compensation by year and by defendant are reported in Figure 22.

Figure 20: Regression Estimate of Undercompensation to Class

All-Salaried Employee Class

Observation: Employee ID record in December of each year
Dependant Variable: Log(Total Annual Compensation/CPI)

Variable	Estimate (1)	St. Error (2)	T-Value (3) (1)/(2)
1. Conduct * Age	0.0067 ***	0.0005	14.1138
2. Conduct * Age^2	-0.0001 ***	0.0000	-14.0235
3. Conduct * Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0028 ***	0.0008	3.6947
4. Conduct	-0.1647 ***	0.0100	-16.5007
5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6949 ***	0.0054	127.9743
6. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7404 ***	0.0027	278.6889
7. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4945 ***	0.0017	291.4208
8. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6690 ***	0.0024	282.4408
9. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.7090 ***	0.0058	123.0243
10. PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6944 ***	0.0069	100.1556
11. LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.8131 ***	0.0363	22.4035
12. ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.2963 ***	0.0053	55.9130
13. APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2610 ***	0.0027	95.3635
14. GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3732 ***	0.0016	228.3877
15. INTEL * Log(Total Annual Compensation/CPI) (-2)	0.3001 ***	0.0023	130.2277
16. INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2551 ***	0.0056	45.7056
17. PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.1983 ***	0.0067	29.5094
18. LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.1779 ***	0.0367	4.8520
19. Log(Age) (Years)	-0.3591 ***	0.0415	-8.6468
20. Log(Age)^2	0.0394 ***	0.0056	6.9805
21. Log(Company Tenure) (Months)	0.0107 **	0.0050	2.1371
22. Log(Company Tenure)^2	-0.0012 **	0.0006	-2.1619
23. Male	0.0027 ***	0.0005	4.9116
24. DLog(Information Sector Employment in San-Jose)	1.4353 ***	0.0147	97.4954
25. Log(Total Number of Transfers Among Defendants)	0.0961 ***	0.0015	63.7243
26. Year (trend)	-0.0038 ***	0.0003	-14.3189
27. Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0154 ***	0.0009	16.6057
28. Log(Total Number of New Hires)	-0.2485 ***	0.0021	-116.9807
29. Log(Firm Revenue Per Employee/CPI) (-1)	-0.1070 ***	0.0035	-30.1447
30. DLog(Firm Revenue Per Employee/CPI) (-1)	0.2170 ***	0.0033	66.3627
31. APPLE	0.0627 ***	0.0162	3.8765
32. GOOGLE	1.0364 ***	0.0174	59.6506
33. INTEL	0.1522 ***	0.0146	10.4453
34. INTUIT	0.1462 ***	0.0193	7.5835
35. LUCASFILM	0.1352 ***	0.0481	2.8127
36. PIXAR	0.7251 ***	0.0422	17.1808
37. Location (State) Indicators	YES		
38. Constant	YES		
R-Square	**0.926**		
Observations	**504,897**		

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.
(2) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.
(3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
(4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of employees, both obtained from SEC Filings. Lucasfilm revenues were obtained from PrivCo and public sources.
(5) Observations are restricted to cases in which there was no change in employer in the previous two years.

Source: Defendants' employee compensation data; St. Louis Fed Reserve; SEC Filings; PrivCo and public sources.

Figure 21: Data Definitions

	Variable	Description
	(1)	(2)
1.	Total Annual Compensation	Sum of base annual salary as of December, total bonuses, overtime amount and equity compensation received in the year
2.	CPI	U.S. Consumer Price Index (St. Louis Federal Reserve)
3.	Conduct	Indicator defined as a fraction of the year the defendant had an active cold-calling agreement
4.	Age	Age of the employee in years
5.	Number of New Hires In the Firm	Number of employees newly hired in the year (i.e. not counting individuals who might have been previously employed in the company)
6.	Company Tenure	Number of months an employee has been affiliated with the company
7.	Male	Indicator for male employees
8.	Information Sector Employment in San Jose	Employment in San Jose/Santa Clara Valley in the Information Sector (St. Louis Federal Reserve)
9.	Total Number of Transfers Among Defendants	Total number of employees who moved from one defendant to another in the year
10.	Total Number of New Hires	Total number of original employees hired by all defendants in the year
11.	Firm Revenue Per Employee	Global revenue of the company divided by global employment in the company (SEC Filings; PrivCo; and public sources)

Figure 22: Estimated Impact on Class Total Compensation

Annual Undercompensation Percentages
All-Salaried Employee Class

	ADOBE	APPLE	GOOGLE	INTEL	INTUIT	LUCASFILM	PIXAR
2005	-1.61%	-1.59%	-1.78%	-1.67%		-12.13%	-10.56%
2006	-4.28%	-4.43%	-4.44%	-4.70%		-14.63%	-12.44%
2007	-6.64%	-6.94%	-6.39%	-7.46%	-3.24%	-17.24%	-14.28%
2008	-9.08%	-9.56%	-8.40%	-10.05%	-5.64%	-19.94%	-15.76%
2009	-9.15%	-9.73%	-7.51%	-9.95%	-5.70%	-20.12%	-14.65%

Source: Regression Estimates of Undercompensation to All-Salaried Employee Class.

147. I performed the same analysis for the set of employees in the Technical Employee Class. The regression model for this Technical Employee Class is reported in Figure 23 and the corresponding damage estimates in Figure 24.

Figure 23: Regression Estimate of Undercompensation to Technical Employee Class

Technical, Creative and R&D Class

Observation: Employee ID record in December of each year
Dependant Variable: Log(Total Annual Compensation/CPI)

Variable	Estimate (1)	St. Error (2)	T-Value (3) (1)/(2)
1. Conduct * Log(Age)	0.0079 ***	0.0007	11.6667
2. Conduct * Log(Age)^2	-0.0001 ***	0.0000	-11.4844
3. Conduct * Log(Number of New Hires In the Firm/Number of Employees(-1))	-0.0121 ***	0.0010	-11.5872
4. Conduct	-0.2196 ***	0.0140	-15.6471
5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6744 ***	0.0073	92.4832
6. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7234 ***	0.0037	197.6595
7. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4367 ***	0.0022	200.6585
8. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6401 ***	0.0030	215.3504
9. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6703 ***	0.0085	79.1708
10. PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6491 ***	0.0106	61.3919
11. LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.8462 ***	0.0692	12.2257
12. ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3053 ***	0.0071	42.7525
13. APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2538 ***	0.0038	67.0286
14. GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3659 ***	0.0021	174.3271
15. INTEL * Log(Total Annual Compensation/CPI) (-2)	0.3179 ***	0.0029	110.4491
16. INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2857 ***	0.0082	34.8914
17. PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.1045 ***	0.0097	10.8013
18. LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.1448 **	0.0693	2.0884
19. Log(Age) (Years)	-0.5894 ***	0.0588	-10.0182
20. Log(Age)^2	0.0696 ***	0.0080	8.7006
21. Log(Company Tenure) (Months)	0.0297 ***	0.0068	4.3581
22. Log(Company Tenure)^2	-0.0025 ***	0.0008	-3.3821
23. Male	0.0065 ***	0.0008	7.8837
24. DLog(Information Sector Employment in San-Jose)	1.4378 ***	0.0204	70.3710
25. Log(Total Number of Transfers Among Defendants)	0.0973 ***	0.0020	47.5566
26. Year (trend)	-0.0008 **	0.0004	-2.1643
27. Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0240 ***	0.0013	18.6766
28. Log(Total Number of New Hires)	-0.2720 ***	0.0029	-92.8937
29. Log(Firm Revenue Per Employee/CPI) (-1)	-0.0661 ***	0.0049	-13.4914
30. DLog(Firm Revenue Per Employee/CPI) (-1)	0.2068 ***	0.0044	46.8319
31. APPLE	0.1220 ***	0.0245	4.9879
32. GOOGLE	1.3682 ***	0.0259	52.7958
33. INTEL	0.1569 ***	0.0219	7.1705
34. INTUIT	0.1393 ***	0.0315	4.4202
35. LUCASFILM	0.0127	0.1037	0.1226
36. PIXAR	1.5864 ***	0.0771	20.5741
37. Location (State) Indicators	YES		
38. Constant	YES		
R-Square	**0.874**		
Observations	**292,489**		

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.
(2) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.
(3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
(4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of employees, both obtained from SEC Filings. Lucasfilm revenues were obtained from PrivCo and public sources.
(5) Observations are restricted to cases in which there was no change in employer in the previous two years.

Source: Defendants' employee compensation data; St. Louis Fed Reserve; SEC Filings; PrivCo and public sources.

Figure 24: Estimated Impact on Technical Employee Class Total Compensation

Annual Undercompensation Percentages
Technical, Creative and R&D Class

	ADOBE	APPLE	GOOGLE	INTEL	INTUIT	LUCASFILM	PIXAR
2005	-1.56%	-1.90%	-3.07%	-1.64%		-10.80%	-9.28%
2006	-4.29%	-4.96%	-7.23%	-3.06%		-14.77%	-10.47%
2007	-6.48%	-7.79%	-9.36%	-3.38%	-3.41%	-18.08%	-10.61%
2008	-8.80%	-10.64%	-11.20%	-4.76%	-5.21%	-20.44%	-11.87%
2009	-8.44%	-10.51%	-9.00%	-4.19%	-4.96%	-20.54%	-9.62%

Source: Regression Estimates of Undercompensation to Technical, Creative, and R&D Class.

148. Accordingly the undercompensation figures resulting from the estimation of this econometric model of employee compensation (as reported in Figure 22 and Figure 24 can be used in a straightforward formulaic fashion in conjunction with the All-Employee Class and Technical Employee Class compensation data (as reported in Figure 3 and Figure 4) to calculate damages for employees in either the All-Employee Class or the Technical Employee Class.

V. Conclusion

149. I therefore conclude that common proof, in the form of documents, data, economic theory, and statistical methodologies, is capable of demonstrating that the Non-Compete Agreements artificially suppressed compensation of all or nearly all members of the All-Employee Class and Technical Employee Class. I conclude further that reliable econometric methods are capable of computing

the total amount of salary suppression caused by the Non-Compete Agreements to Members of the All-Employee Class and Technical Employee Class .

Edward E. Leamer, Ph.D.
October 1, 2012

APPENDIX A. Defendant Data Relied Upon

A. Description of Data Requested and Produced

150. Defendants produced two types of data: employee compensation and hiring and recruiting data. Employee compensation data contains compensation information for salaried employees that were active during the period of January 1, 2001 through February 1, 2012 at each defendant.[173] Hiring and recruiting data contains job applicant information for all potential candidates during the period of January 1, 2001 through February 1, 2012 for each defendant.

1. Employment Data

151. Plaintiffs requested each defendant produce compensation histories for all salaried employees that were active during the period of January 1, 2001 through February 1, 2012. The information requested includes personal information (an encrypted social security number allowing employees to be matched across defendants, hire date, previous employer information, birth year, gender, education level, and channel of hiring) and on-going job information (job title and level, salary, bonus awards, benefits, stock option grants, office location, and manager ID). Additionally plaintiffs requested employee information that identifies drivers of compensation (information regarding changes in titles or jobs within a company) and exit information for employees that were terminated.

2. Recruiting Data

152. Plaintiffs requested each defendant produced recruiting data for the period of January 1, 2001 through February 1, 2012. The information contained in the recruiting data should consist of application date, applicant's resume information (employer, job title, and education level), the source through which

[173] Employees can be "exempt" or "non-exempt". See e.g., 76512DOC000638-677 at 641. Exempt workers are salaried and generally not entitled to overtime pay. They generally have advanced professional training or a degree. Class members are salaried and so are generally exempt.

the application originated (cold called by recruiter, applied on website, etc.), and outcome (hired, rejected, etc.).

153. Additionally, plaintiffs requested that defendants provide detailed Cold-Calling data for the period of January 1, 2001 through February 1, 2012. The information contained in the Cold-Calling recruiting data should consist of a unique identifier for each candidate contacted, date of contact, and candidate's resume information (employer, job title, education level, experience), the source through which the application originated (cold called by recruiter, applied on website, etc.), and outcome (hired, rejected, etc.). Though some defendants have produced some of their candidate tracking information, they have yet to produce enough information to determine Cold-Calling activities.

B. Datasets Created for Analysis

154. Compensation data from all defendants was cleaned and processed in order to generate a Master Employee dataset with monthly compensation and employee information for 2001 - 2012. The information included in the master dataset includes each person's hashed SSN, employer and job title for each month in 2001-2012 for which a person is employed by one of the defendants, person's information (age, gender), original and current hire dates, termination dates, tenure of employment, annual performance evaluation score, dates of changes in salary and title, previous employer information, department, job grade and job family information, leave of absence dates, annualized base compensation, bonus compensation, stock options and equity compensation,[174] overtime compensation for non-exempt employees, and employee status identifiers (FLSA status, part time and full time identifiers, temporary employee identifiers, etc.).

[174] To compute employee stock compensation, the 'Weighted average grant date fair value' for stock options and restricted stock as reported by the defendants in their annual SEC filings was multiplied by the number of options or restricted stock units granted to the employee.

APPENDIX B. Definition of the Technical Employee Class

155. I was asked to identify employees that fit with in Technical Employee Class, defined to include all full-time salaried employees of Defendants during the period of the alleged agreements (see Figure 1) that worked in technical, creative, and research & development positions. The following job descriptions were included within this Technical Employee Class :

1. Software Engineers,
2. Hardware Engineers and Component Designers,
3. Application Developers,
4. Programmers,
5. Product Developers,
6. User Interface or User Experience Designers,
7. Quality Analysts,
8. Research and Development,
9. Animators, Digital Artists, Creative Directors and Technical Editors,
10. Graphic Designers and Graphic Artists,
11. Web developers,
12. IT professionals,
13. Systems engineers and administrators, and
14. Employees classified as technical professionals by their employers.

The Technical Employee Class does not include the following types of employees:

1. Non-technical employees (marketing, accounting, finance, operations, etc.)
2. Senior executives,

3. Non-US employees,

4. Network administrators,

5. Systems support/maintenance personnel,

6. Facilities maintenance employees, or

7. Manufacturing technicians.

156. Several defendants provided a "Job Family" designation with their employment data. The majority of class members fall under the job families listed in Figure 25 below.

Figure 25: Adobe, Apple, Google, Intel, and Intuit Creative, Technical, and R&D Job Families

Adobe	Apple	Google	Intel	Intuit
RSCH & DEV	IS&T	ADSALES_CSE	CAD ENGINEERING	APPLICATIONS
	R&D	ENG_DEV_ADV	COMPONENT DES ENGINEERING	CREATIVE DESIGN
		ENG_MEMBER	ELECTRONIC ENGINEERING	DATA ADMIN-ANALYST
		ENG_PROG	ENGINEERING	DATABASE ADMINISTRATION
		ENG_RES	ENGINEERING MANAGEMENT	DESKTOP SYSTEMS
		ENG_SOFT	HARDWARE ENGINEERING	DEVELOPMENT MANAGEMENT
		ENG_SOFT_MGR	INFORMATION DATA ANALYSES	DOCUMENTATION
		ENG_SQAE	INFORMATION NETWORKS	INFORMATION SECURITY
		ENG_SRE_SWE	INFORMATION SERVICES	INFORMATION TECHNOLOGY
		ENG_SRE_SYSADMIN	INFORMATION TECH MANAGEMENT	INTERACTION DESIGN
		ENG_TECH_WRITERS	MASK DESIGN	IT
		ENG_TECHPROG	MECHANICAL ENGINEERING	IT MANAGEMENT
		ENG_UI	MKTG ENGINEERING MANAGEMENT	NETWORK ADMINISTRATION
		ENG_USAB	PROCESS ENGINEERING	NETWORK ENGINEERING
		ENT_ESO	PRODUCT ENGINEERING	PRODUCT DEVELOPMENT MGMT
		ENT_SE	PROGRAMMING	PRODUCT MANAGEMENT
		MKTG_CREATIVE	PROJ/PROG MANAGEMENT	QA ENGINEERING
		ONLINE_SALES_TECH_OPS	QUALITY ENGINEERING	SCM ENGINEERING
		OPS_DCFAC_ENG	RESEARCH & DEVELOPMENT	SOFTWARE ENGINEERING
		OPS_NET	RESEARCH ENGINEERING	SOFTWARE QA ENGINEERING
		OPS_SYS	SOFTWARE ENGINEERING	SYSTEMS
		OPS_TECH	SYSTEMS ENGINEERING	USER INTERFACE DESIGN
		SALES_ENG	SYSTEMS SUPPORT	WEB DEVELOPMENT
		SALES_TSE	TECH	WEB ENGINEERING
			TECH MARKETING ENGINEERING	WEB PRODUCTION
			TECHNICAL	
			TECHNICAL WRITING	
			TEST ENGINEERING	

Source: Defendants' employee compensation data

157. There are additional Technical Employee Class members who fall under other categories. Additional criteria were taken to select class titles:

a. Adobe

Employees classified by Adobe as "Technical Professionals" based on the field "AAP Code Description" in its compensation data as well as the "Business Unit" and "Function Name" fields were included in the Technical Employee Class.[175]

b. Apple

Non-facilities engineers, web developers, graphic designers, and other technical titles not classified as part of the R&D or IS&T job families were included in the Technical Employee Class. All R&D and IS&T support titles (librarian, technicians, etc.) were excluded.

c. Google

Google identifies technical employees by job grade levels beginning with "T".[176] Additionally, technical employees in operating and support fields such as IT, Systems, as well as web designers, application developers and other creative and technical roles were included in the Technical Employee Class. Excluded from the Technical Employee Class were support roles (e.g., tech support and desktop support).

d. Intel

Intel identifies technical employees through their job families. Additional job families included in the Technical Employee Class were all non-facilities engineering job families, as well as graphic and web design and developer families. Excluded were non-technical roles as well as manufacturing technicians and machinery operators.

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[175] See Adobe compensation data (FY2001_HighlyConfidentialAEO-FY2012_HighlyConfidentialAEO).

[176] GOOG-HIGH TECH-00057189.

e. Intuit

Intuit identifies technical employees through their job families. Additional job families included in the Technical Employee Class were all software engineering and application developer families, non-facilities engineering job families, as well as graphic and web design and developer families. Excluded were non-technical roles as well system support and technician roles.

f. Lucasfilm and Pixar

Neither Lucasfilm nor Pixar provided job families to identify creative, R&D, and technical employees. For both cases, class members were selected on the basis of their job titles.[177] Employees were identified as Technical Employee Class members if their titles identified them as Animators, Artists, Software Engineers, Engineers, Scientists, Researchers, R&D professionals, Technical Directors, Designers, Modelers, or IT and Systems staff. Excluded from the list were videographers, camera operators, technicians and system support employees. Lucasfilm employees prior to 2006, for whom we are missing job title information, are identified as being in the Technical Employee Class if their titles in the 2006-2012 compensation data are flagged as Technical Employee Class titles.

[177] Pixar did provide department information that groups technical roles such as the Studio Tools group, the Systems group, and others as well.

EXHIBIT C

to Edward Leamer's 10/28/13 Merits Report

[REDACTED/PUBLIC VERSION]

IN THE UNITED STATES DISTRICT COURT
FOR THE NORTHERN DISTRICT OF CALIFORNIA
SAN JOSE DIVISION

CONFIDENTIAL – TO BE FILED UNDER SEAL
SUBJECT TO PROTECTIVE ORDER

IN RE: HIGH-TECH EMPLOYEES ANTITRUST LITIGATION **THIS DOCUMENT RELATES TO:** **ALL ACTIONS**	**No. 11-CV-2509-LHK**

SUPPLEMENTAL EXPERT REPORT OF EDWARD E. LEAMER, PH.D.

May 10, 2013

TABLE OF CONTENTS

I. Introduction, Assignment, and Summary of Conclusions

1. I have been asked by counsel for Class Plaintiffs in this matter to respond to the following questions regarding my prior analysis and further analysis that can be conducted based on the available data in this case. I have been asked to focus my response on the employees belonging to the proposed Technical, Creative and R&D Class ("Technical Class") identified in my initial report.

2. **Question #1:** Does the total compensation of Technical Class employees in specific job titles move together over time, further confirming the existence of a somewhat rigid pay structure at each Defendant?

3. **Answer:** When asked in the deposition (p283) "Could a nonrigid wage structure, as you've defined it, lead to parallel lines?" I responded to what I thought to be a hypothetical with "Yes, it could." I should have added that this would require highly unusual external labor market conditions which dictated the parallel movements of vast numbers of titles. Markets typically are not so orderly, and prices of, for example, gold, silver, copper and zinc do not normally move in parallel. For that reason, I regard the parallel movements of compensation for so many titles not only to be consistent with a "somewhat rigid wage structure" but also evidence specifically in favor of the hypothesis that internal equity played an important role in determining compensation in all these firms. In this report, I confirm this opinion with two additional empirical studies. I have estimated regression models that allow me to separate the contributions of internal and external forces, and found that the internal forces are evident but the external forces are not. I have also compared average compensation for the Technical Class of titles and the non-technical employees for all the defendants. I found that the compensation curves of these two groups within each firm are highly parallel while the compensation curves for the same group from two different firms move in a much more disparate way. This again is saying that the internal forces are evident but the external forces are more difficult to detect.

4. In this Report, I present correlations that compare the movement *over time* of the average compensation of each title with the average compensation of the firm's Technical Class. To accommodate titles that cannot be accessed on a title-by-

title basis due to insufficient data (approximately 63 percent of Technical Class titles, but representing just 6 percent of Class Period employee-years), I also analyzed correlations of relatively narrow groups of employees (each comprising approximately a tenth of the Technical Class employees of that firm). These correlations are computed for *all* titles, not just 20. They reveal that there is large amount of co-movement of compensation among most of the Technical Class titles of each defendant. These correlations are consistent with a top-down budgeting method in which all members of the firm in any given year receive a common compensation increment, which is adjusted somewhat by title and possibly by individual within the title depending on specific circumstances. The evident, substantial, common, firm-wide component of compensation is what creates what I previously called a "somewhat rigid" salary structure, which allows the effects of the anti-cold-calling conspiracy to spread broadly across each firm.

5. **Question #2:** Do the data show additional evidence that internal factors such as internal equity partly drove the Defendants' compensation structures, as opposed to only external market forces?

6. **Answer:** I have analyzed a model of sharing of compensation effects, title by title, within Defendant firms relative to movements of other Technical Class employees compensation. Again, to accommodate titles that cannot be accessed title-by-title (approximately 70 percent of Technical Class titles, but representing just 8.4 percent of Class Period employee-years), I also analyzed the compensation of relatively narrow groups of employees against the compensation of the overall Technical Class employees.

7. Specifically, I report below estimated multiple regression models that explain the year-by-year increases in average compensation at the title level in terms of four explanatory variables: (1) increases in average Technical Class compensation; (2) the previous year's ratio of average Technical Class compensation divided by the average title compensation; (3) the previous year's ratio of firm-wide average revenue divided by the average title compensation; (4) the percent change in software jobs in the San Jose-Sunnyvale-Santa Clara Metropolitan Statistical Area (hereafter: San Jose MSA).

8. I find that the vast majority of individuals fall within titles or groups that show 1) positive contemporaneous sharing of compensation effects, and 2) sharing across time that would spread gains in compensation across other job titles. This is consistent with my previous opinion that all or almost all Defendants' employees would have been impacted by the non-compete agreements. Furthermore, the sharing of gains over time strongly indicates the existence of an internal sharing force driving the structure of class member compensation, rather than only external market forces.

9. **Question #3:** Do the data show the existence of large groups of class members who necessarily would not have been harmed by a restriction on cold-calling?

10. **Answer:** No. I have performed the above-mentioned statistical analyses separately for distinct subgroups of employees grouped by compensation level. I do not find persuasive evidence to suggest that there are sizeable groups whose compensation might have been disconnected from Defendants' somewhat rigid compensation structure. The correlation and regression analysis I performed in this regard show ripple and spillover effects across employees in very different roles. The analysis shows that when each title or group is studied separately, on a case-by-case basis, it is found that, compensation almost always moves with the collection of other titles or groups. All these groups, no matter how much they differ in the job titles they contain, are found to be tied closely together.

11. **Question # 4:** Is it possible to identify and exclude from the Technical Class job titles based on a lack of these positive correlative relationships?

12. **Answer:** No. Although the vast majority of titles exhibit strong positive correlations with the overall Technical Class, there certainly are exceptions. One might consider titles with negative correlations with the overall Technical Class to be candidates for exclusion from the class. However, this is not justified statistically because statistical variability can cause some negative correlation estimates among the thousands of titles even if all the true correlations are positive. An appropriate statistical model for this kind of data allows some pooling of evidence across titles, and when this is done the analysis indicates that corrected estimated of many of these negatives is positive. In other words,

it matters for interpreting the evidence about each title that the vast majority of estimated correlations are positive.

13. In sum, the statistical analysis I conduct here--in conjunction with the economic and econometric evidence in my original reports--supports my original finding of a somewhat rigid pay structure at each Defendant that would have transmitted the effects of the agreements broadly, including throughout the Technical Class.

II. Defendants' Use of Compensation Structures

14. Most, if not all, of these defendants subscribe to services that are intended to provide them information about "market" prices for various jobs. Such information helps them keep compensation packages in line with the external opportunities, with or without the imminent threat of loss of an employee. However, these external sources provide broad industry averages with limited relevance and reliability. Regardless of what these services suggest, their information cannot compare with the information conveyed by an actual outside offer. That can ring off a loud alarm that is heard all the way up to the CEO.

15. The information by an outside offer or even a cold call can stimulate a response by management that can go much beyond the specific individual directly affected. A chain of similarities can transmit a bump in compensation for a single individual broadly across a firm for two reasons. First, when management becomes aware of an attractive outside opportunity for one individual this may make management aware also of the implicit competitive threat to similar individuals and management may feel it wise to make a preemptive move against that threat by an increase in compensation for these newly-threatened similar employees. Though the "market" does not require a bump in compensation for these similar individuals until they actually receive an outside offer, preemptive action can minimize the disruption to employee loyalty that might occur when an employee discovers that he or she had been "unfairly" undercompensated. A broad preemptive response is completely analogous to salary increases that are tied to information provided by

employment services regarding the compensation offered by the "market." These responses are broad and not necessarily individual-based.

16. Similarity in worth is one reason why salaries can be tied together. Fairness is the second reason why a bump in compensation for a single individual can be transmitted broadly across a firm. A critical problem with "market-based" individual compensation is that the productivity of each worker in most salaried jobs is difficult to determine with accuracy, yet the range of achieved productivity can be broad. Firms need to use HR policies that encourage high levels of productivity. The highest levels of productivity come from contented employees who are committed to the mission of the enterprise. In order to maintain or to increase the contentment and commitment, it is essential for management to treat employees "fairly." As discussed in the paragraph above, a strictly market view of employee compensation doesn't require an increase in salary of any individual until an outside threat actually materializes, but the force of "fairness" can necessitate preemptive increases in compensation. In addition, employees are likely to have their own views of job and performance similarity, and these employees can have their productivity adversely affected if they perceive that some employees are receiving "unfairly" high compensation compared with them.

17. Fairness is a matter of personal opinion and there is no sure way to know exactly who feels equivalent to the employee who got that bump in compensation and who doesn't really care. The title and grade structure of compensation may reflect management's views of what is fair and it may influence the perception of similarity that determines employee fairness beliefs. This is the reason why companies tend to follow guidelines laid out in terms of salary ranges, so employees can be assured that their compensation falls within reasonable range of their colleagues.

III. Empirical Methodologies for Exploring the Somewhat Rigid Salary Structure

A. Choice of Aggregation Level

18. The data set I explore is composed of compensation records of salaried individuals on the payrolls of the Defendants. These individuals are grouped by the Defendants by title and (for some of the Defendants) the titles are grouped by grade. Based on instructions from counsel regarding the employees in the Class, except for Lucasfilm I limit the inquiry to the titles that have been identified as Technical Class titles.[1]

19. These data could be studied at the individual level, at the title level or some more aggregated groups. I have chosen to work first with the title averages, because the individual data is likely to be dominated by forces that operate at the individual level, which can make it difficult to detect the firm wide effects including the spread of the anti-cold-calling agreements broadly across the firms. Averaging across individuals in a title can average out the individual effects, thus making the firm-wide effects more transparent. In addition, a title-level analysis provides a clearer perspective on the compensation structures the documentary evidence shows Defendants used to manage their many employees and maintain internal equity among their employees.

20. I have discovered that the title-by-title analysis works well for many titles but there are some titles that were used only briefly, and there are other titles that are sparsely populated and that seem much influenced by the idiosyncratic individual behavior which still masks the firm-wide effect that I am seeking to estimate. The data set contains only eleven annual observations which is adequate for the statistical work, but not plentiful. Titles that have fewer annual observations tend to produce what statisticians call "statistically insignificant" results, meaning the data sets are too small to yield accurate estimates. This is particularly troublesome for Apple which had a title restructuring in 2005 and

[1] Because Lucasfilm did not provide title data prior to 2006, there are insufficient years of data unless the inquiry is expanded to cover all Lucasfilm employees. Hence, the analysis presented below is limited to Technical Class for all Defendants, expect Lucasfilm, for whom it applies to all employees.

for Lucasfilm which did not provide titles prior to 2006. In addition titles that include just a few individuals may not benefit much from the averaging across individuals and furthermore, unlike the individual data, the title compensation for sparsely populated titles can vary wildly as individuals come and go. I give some examples below of Adobe titles with highly variable headcounts and highly variable median ages.

21. To deal with the limitations of the title-by-title data, I also include the same type of statistical work but applied to ten groups of titles in each firm. I have formed the ten groups of titles by ordering the titles by average base compensation and then splitting the titles into ten deciles (based on the number of employee-years).[2]

B. Correlation Analysis of Compensation Structure

22. Economists often look to correlation coefficients to measure statistically how closely different variables move together. Correlation coefficients range in absolute value from 0 to 1. One indicates perfect correlation, zero indicates no relationship. The sign on the correlation indicates whether or not the series in question move in the same direction. I begin my analysis of Defendant compensation structures with compensation correlations.

23. There are two types of correlations relevant for determining if the compensation movements of two series are similar: correlation of compensation levels and correlations of compensation *changes*. The correlations of the log of the levels of compensation emphasize longer run movements and the correlations of the change in the log of the levels focus on year-by-year movements.

C. Regression Analysis of Compensation Structure

24. Correlation of title compensation and class compensation could come from sharing effects but could also come from third variables that operate on both

[2] For several Defendants, certain large titles made splits into ten groups impractical. In those cases a smaller number of groups was used.

title and class compensation at the same time, for example, "market forces." To confirm the existence of a somewhat rigid compensation structure revealed by my correlation analysis, I examine (company by company) a multiple regression model which forces the class compensation to compete with other variables as an explanation of title compensation.

25. This regression model explains increases in title average real (inflation adjusted) total compensation and includes the increase in class average real total compensation as one of four explanatory variables.[3] By including the increase in class compensation in the equation, the regression encompasses the correlation analysis of these two variables. In the multiple regression setting, this variable allows us to determine at a particular defendant the extent to which title and class compensation move together, *after controlling for the other variables in the equation*, in particular, after controlling for "market forces." If the coefficient of this variable were equal to one, then the employee would inherit 100 percent of the class compensation changes and in that sense the two would be closely tied together. This is the first sharing effect.

26. The regression model includes a second sharing variable, which is the ratio of class compensation to title compensation in the previous year. While the first sharing effect measures the extent to which the two compensation levels move together, the second measures the extent to which corrective action is taken at the company when they move apart. If the coefficient is positive on this variable it means that following periods in which the class average compensation at the company is abnormally high compared with the title, the title tends to get a special increase in compensation to bring it back in line with the class

27. The regression model requires both of these sharing variables to compete against two other determinants of title compensation at the company. One of these other variables is the previous year's ratio of firm-wide average revenue divided by the average title compensation. This variable allows us to determine

[3] For each title regression I exclude from the class average real total compensation, the compensation of the title itself.

which titles, if any, share increases in firm revenue overall. It might be expected that critical technical and creative workers are the ones who would have revenue sharing relationships with their firms since they may have an accentuated effect on the firm's success.

28. The fourth variable is the percent growth in software jobs in the San Jose- MSA. This the external job market variable which is intended to reflect how hot or cold was the technical job market generally, not just in the San Jose MSA.

29. I illustrate this regression in Figure 1, as estimated for one Intel title.[4] In this example, the two coefficients for the two sharing variables are positive, meaning that workers with this title can expect to receive a compensation increase if 1) there are general increases in the compensation of other Technical Class titles at the firm, and 2) a title that received a relatively small percent increase relative to other Technical Class titles at the company last year will tend to receive a larger increase in subsequent years. This indicates a positive sharing and internal equity effect. Both the contemporaneous and lagged coefficients suggest that internal equity forces move in a fashion that helps align worker's compensation together with that of employees in other roles at the firm.

[4] As mentioned before this regression is estimated separately for each title and company. Titles that do not afford a sufficient number of observations (6 observations, or 7 consecutive years) are treated as 'Not Estimated' and are excluded from the coefficient distribution calculations presented in this report.

Figure 1

Illustrative Example of Compensation Sharing Regression Model
Intel Named Plaintiff Title SOFTWARE_ENGINEER_7

Variable	Coefficient	Std.-Error	T-value	P-value
(1)	(2)	(3)	(4)	(5)
Dependant Variable				
DLog(Title Average Annual Total Compensation)				
Contemporaneous Effect Variable				
DLog(R&D Average Annual Total Compensation)	0.784 ***	0.064	12.238	0.000
Lagged Effect Variable				
Log((R&D Avg Annual Total Comp (-1) / (Title Avg Annual Total Compensation (-1)	0.251 *	0.098	2.562	0.051
External Forces Variables				
Log((Firm Revenue Per Employee (-1) / (Title Avg Annual Total Compensation (-1)	-0.032	0.094	-0.346	0.743
DLog(San-Jose Information Sector Employment)	0.092	0.126	0.731	0.498
Constant	-0.223	0.541	-0.411	0.698
Observations	10			
R-squared	0.986			

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.
(2) Title Average Compensation is computed as the average of title employee's annual total compensation. R&D Avg Total Comp is computed over all Technical, Creative and R&D employees other than the tilte itself
(3) All Compensation Variables are Inflation Adjusted

Source: Defendants' employee compensation data

IV. Results of Title Based Correlations and Multiple Regressions

A. Title-by-Title Correlation Analysis of Compensation Structure

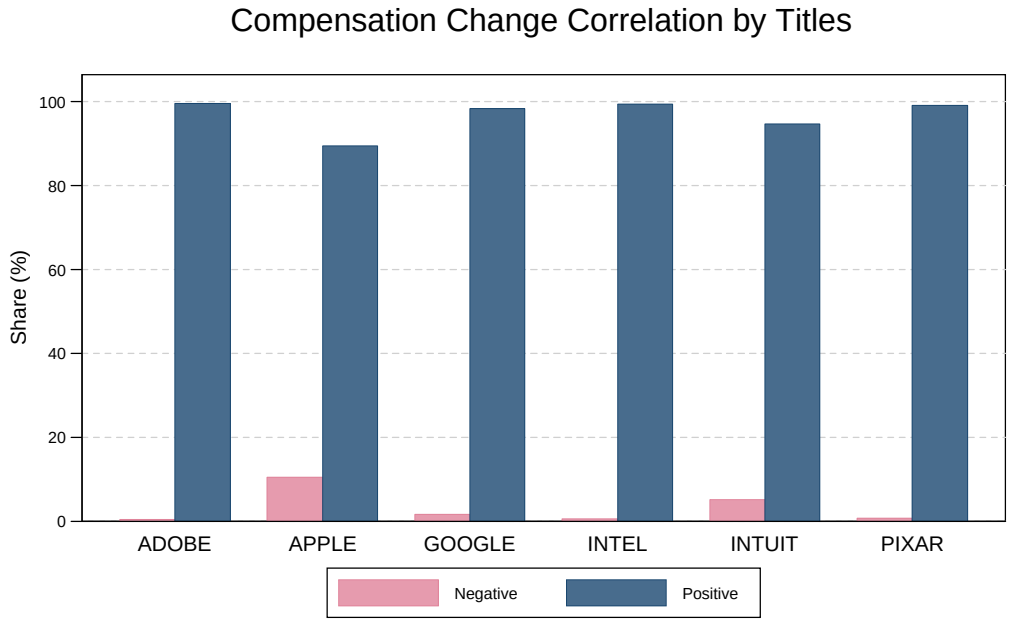
30. The correlations for all Defendants are reported in Exhibit 1 (Adobe) and Exhibit 2 (other Defendants). Below I will discuss the Adobe results in detail, but here it is enough to summarize the overall results with Figure 2 and Figure 3, which indicate the fractions of titles (weighted by employee years) with positive correlations between title compensation and Technical Class compensation at the same firm, restricted to titles with six or more annual

observations. The titles with five or fewer tend to produce a more extreme distribution of correlations.

31. Although there are some negative estimated correlations, that does not mean that any true correlations are negative. These estimates are computed with statistical error which is large enough to produce some negative estimates among the thousands of titles included even if all true correlations were positive.

32. Moreover, the fact that the vast majority of cases are positive is strong support for the conclusion that all the true correlations are positive. There are formal statistical methods that allow pooling of results across titles based on the assumption that the titles probably have similar correlations. These methods would shrink the estimates for each title toward the mean across all titles, which is of course positive. Once this shrinkage is done, the results indicate that for many of these negatives the corrected results will be positive, strengthening the conclusion that all titles in the class share movements with the class overall.

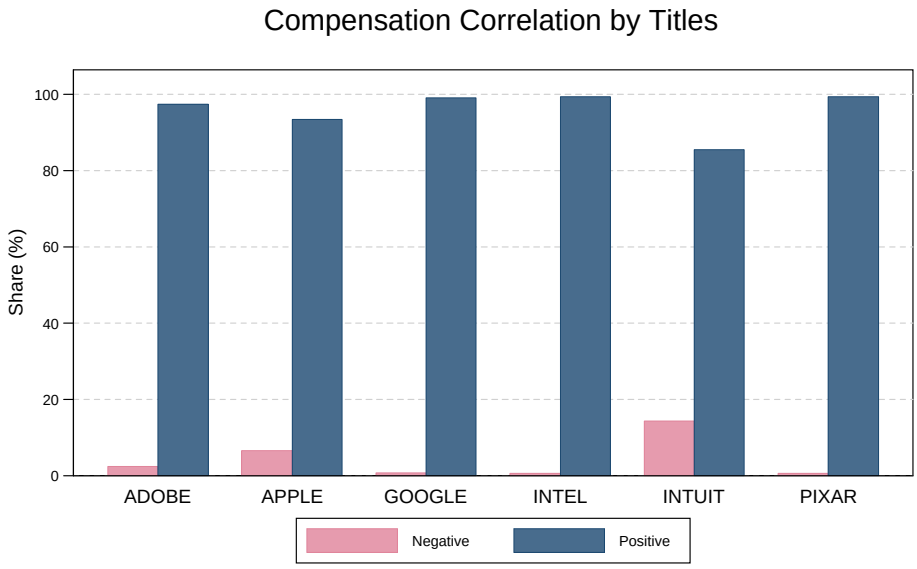
Figure 2: Large Share of Change Correlations are Positive



Source: Defendant Employee Compensation Data; Correlation Analysis

Note: Distribution of growth in avg compensation correlation over titles with six or more years of data.
Weighted by class-period employee years

Figure 3: Large Share of Level Correlations are Positive



Source: Defendant Employee Compensation Data; Correlation Analysis

Note: Distribution of log avg compensation correlation over titles with six or more years of data.
Weighted by class-period employee years

33. It is not just statistical variability that can explain the negative or small correlations. Changes in the composition of employees within a title as employees come and go can cause changes in title compensation and mask the normal correlation with the class overall. I will illustrate this point below with a close examination of some of the Adobe titles that have low or negative correlations with the class.

Figure 4

Summary of Compensation Change Correlation

	Positive Sign		Negative Sign		
Employer	Significant	Not Significant	Significant	Not Significant	Total
	(Percent)	(Percent)	(Percent)	(Percent)	(Percent)
ADOBE	67 %	32 %	0 %	0 %	100 %
APPLE	54	35	1	10	100
GOOGLE	76	22	0	2	100
INTEL	94	6	0	1	100
INTUIT	81	14	0	5	100
PIXAR	86	13	0	1	100

Source: Defendants' employee compensation data; Correlation Analysis
Note: Distribution of growth in compensation correlation over titles with six or more years of data.
Weighted by class-period employee years.

Figure 5

Summary of Compensation Level Correlation

	Positive Sign		Negative Sign		
Employer	Significant	Not Significant	Significant	Not Significant	Total
	(Percent)	(Percent)	(Percent)	(Percent)	(Percent)
ADOBE	92 %	5 %	0 %	3 %	100 %
APPLE	78	16	1	5	100
GOOGLE	83	16	0	1	100
INTEL	85	14	0	1	100
INTUIT	45	40	2	12	100
PIXAR	84	15	0	0	100

Source: Defendants' employee compensation data; Correlation Analysis
Note: Distribution of log avg compensation correlation over titles with six or more years of data.
Weighted by class-period employee years.

B. Title-by-Title Multiple Regressions

34. As described above, I also analyzed a multiple regression model of compensation that explains the year-by-year increases in average compensation at the title level in terms of four explanatory variables: (1) increases in average Technical Class compensation at the firm; (2) the previous year's ratio of average Technical Class compensation at the firm divided by the average title compensation; (3) The previous year's ratio of firm-wide average revenue divided by the average title compensation; (4) the percent change in software jobs in the San Jose MSA.

35. The data set is limited to eleven annual observations from 2001 to 2011, and many titles have fewer observations. A four-variable regression is a heavy burden with such data, which is reflected in the number of statistically insignificant coefficients. The statistically insignificant results are particularly prevalent for the external market effects and the revenue-sharing effects.[5] The two sharing variables have more statistically significant coefficients. In other words, in the competition for statistical significance, it is sharing that wins.

36. I present in Figure 6 and Figure 7, below, class-wide results for titles with at least seven observations (approximately 30 percent of all Technical Class titles and more than 91 percent of their Class Period employee years).

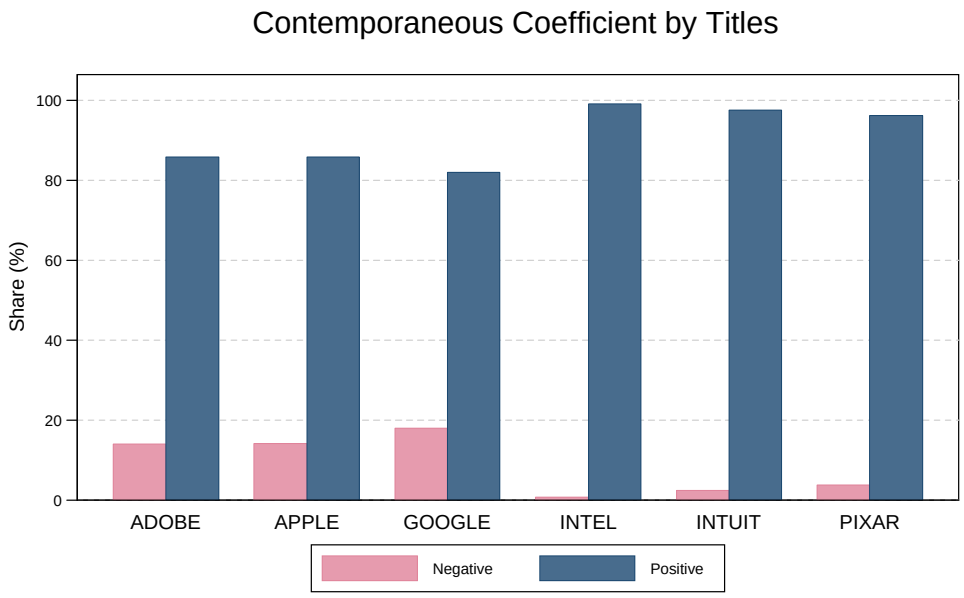
37. Those results show the following. First, the vast majority of titles have a positive sharing effect in either the contemporaneous relationship or the lagged relationship. Second, of those that are negative a small fraction are statistically significant. Third, even these negative results occur in the context of body of evidence that there is a general relationship supported by sharing relationships for the vast majority of titles. Many of these are statistically significant. In sum, this analysis provides support for internal relationships across all Class titles at a

[5] This model is completely appropriate if the sharing force came from the class overall, equally across all titles. If on the other hand, title A were connected only to title B, then my attempt to link A to the class overall would yield a small and probably insignificant effect unless the variability in compensation of the class were largely determined by variability in compensation of title B. To put this in simple terms, the model that I am estimating makes it less likely not more likely to find a sharing effect.

firm that would tend to make impact of the agreements common to all Class members.

38. Thus, the vast majority of these titles have a positive internal equity sharing relationship with other Technical Class titles at the same firm. The implication of these results is to support my previous conclusion that the impact of the alleged non-compete agreements would be common across the class and common across the Technical Class employees in particular.

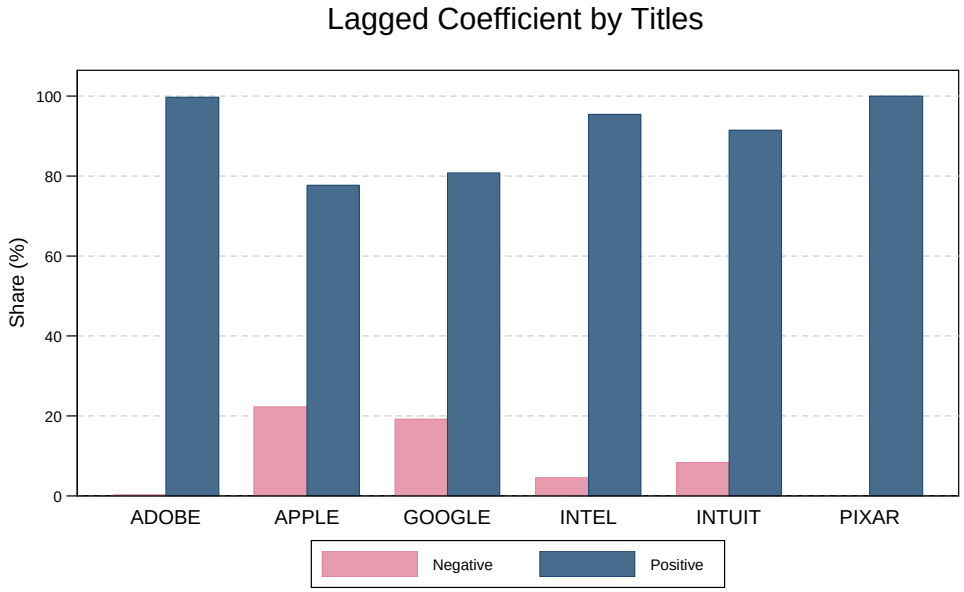
Figure 6: Large Share of Contemporaneous Coefficients are Positive



Source: Defendant Employee Compensation Data; Regression Analysis

Note: Distribution of estimated contemporaneous coefficient over titles with seven or more years of data.
Weighted by class-period employee years

Figure 7: Large Share of Lagged Coefficients are Positive



Source: Defendant Employee Compensation Data; Regression Analysis

Note: Distribution of estimated lagged coefficient over titles with seven or more years of data.
Weighted by class-period employee years

Figure 8

Summary of Contemporaneous and Lagged Net Effect

	Positive Sign		Negative Sign		
Employer	Significant	Not Significant	Significant	Not Significant	Total
	(Percent)	(Percent)	(Percent)	(Percent)	(Percent)
ADOBE	22 %	75 %	0 %	3 %	100 %
APPLE	23	62	0	14	100
GOOGLE	12	69	2	17	100
INTEL	88	11	0	1	100
INTUIT	73	23	0	4	100
PIXAR	60	39	0	0	100

Source: Defendants' employee compensation data; Regression Analysis
Note: Distribution of the sum of estimated contemporaneous and lagged coefficients over titles with six or more years of data.
Weighted by class-period employee years.

39. It may be important to understand that in principle there is a matrix of sharing relationships that connect titles directly affected by the conspiracy with other titles that are tied together with these affected titles. For example, with 101 Adobe titles in the class with six or more observations, this would require potentially the estimation of a 101 by 101 matrix of connections, which is far too many parameters to estimate with only eleven years of data. The regressions that I have estimated have a much simpler structure connecting each title not separately with all of the other titles but instead with the Adobe-wide variables.[6]

40. The regression results for Adobe titles with seven or more years of data are reported in Exhibit 1. The first two Sections give descriptive information about the data and the two correlations. These titles are sorted by the correlations of the log levels of average real compensation (Column 7). Column (9) which is the correlation between the percent change in average real compensation is more relevant here because this correlation is part of the estimated regression.[7] The regression coefficients of the four variables are collected together in Section 3 and the corresponding t-statistics are reported to their right in Section 4.

41. Roughly, a t-statistic in excess of 2 in absolute value is said to produce "statistically significant" estimate by conventional standards. For that reason, t-statistics in excess of 2 are highlighted. Among the titles with eleven years of data it is the two sharing variables that jump out with high t-statistics, more often the "corrective" variable (Column 16) than the class-wide contemporaneous effect (Column 15). The external market variable (Column 18) has a t-value in excess of 2 only 4 of 41 titles, and the revenue variable (Column 17) has one negative and no positive significant t-stats. The results are more mixed deeper into the table as the number of observations diminishes.

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[6] As I noted above, this model looks for a sharing force that comes from the class overall, equally across all titles. If on the other hand, title A were connected only to title B, then my attempt to link A to the class overall would yield a small and probably insignificant effect unless the variability in compensation of the class were largely determined by variability in compensation of title B. The model that I am estimating makes it less likely not more likely to find a sharing effect.

[7] The increment in the fit of the model associated with the last three explanatory variables can be found by comparing the R-sq in the last column with the squared of the correlation.

42. This confirms the summary above, providing direct evidence of sharing across titles. The almost always positive coefficients on the "corrective" variable equal to the lagged ratio of compensation relative to title compensation in the title indicates that if the title compensation departs from its normal relationship with the class, then corrective action is taken to either raise or lower compensation in the title.

V. Decile Based Correlations and Multiple Regressions

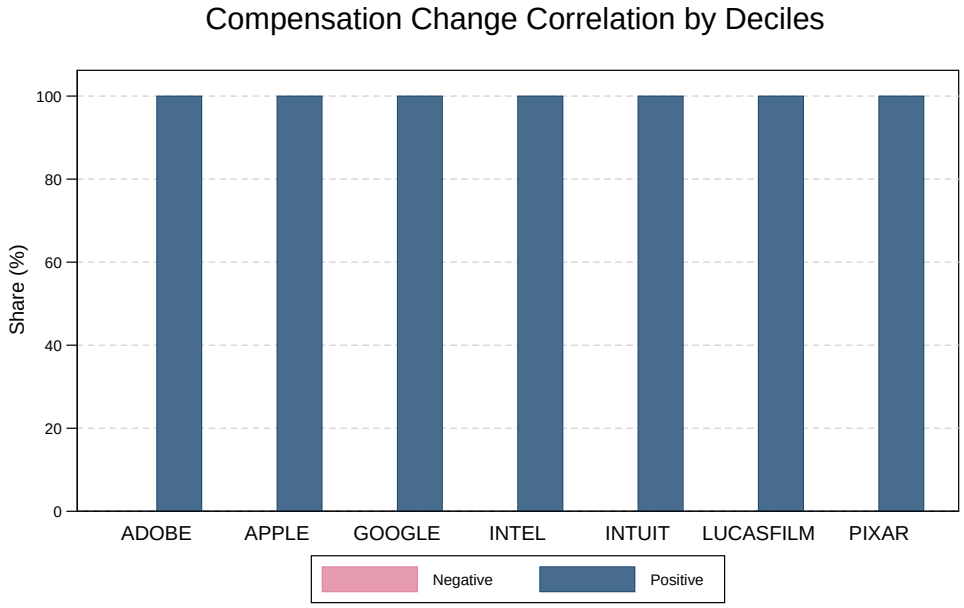
43. The title-based study just described by necessity excludes titles that are infrequently populated. To include these titles in this study, I have formed groups of titles on which to conduct the correlation analysis and the multiple regressions. I split each Defendant's Technical Class titles into ten groups. To form the ten groups, I ranked titles on the basis of average (inflation-adjusted) total compensation over the lifetime of the title and then divided these up into deciles based on employee-years.[8]

A. Decile Based Correlation Analysis

44. The correlation analysis of the ten groups yields strong evidence of both short and long-run compensation structures for each subgroup of the Defendants' Technical Class employees. Figure 9 and Figure 10 indicate the numbers of the ten groups that had positive correlations with the Technical Class: 10 out of 10 for the levels correlation and 10 out of 10 for the percent change correlations. Thus, every group shares in its firm's compensation structure. Every group shows both immediate and long-run correlation structure for every group. This is consistent with and supports my conclusion that the Defendants' compensation was semi-rigid.

[8] Since Lucasfilm did not provide title data, individuals were ranked in a similar fashion for Lucasfilm. Although I attempted to break the firms up into 10 equal sized groups (equal based on employee years), some groups end up being larger than others because of some big titles.

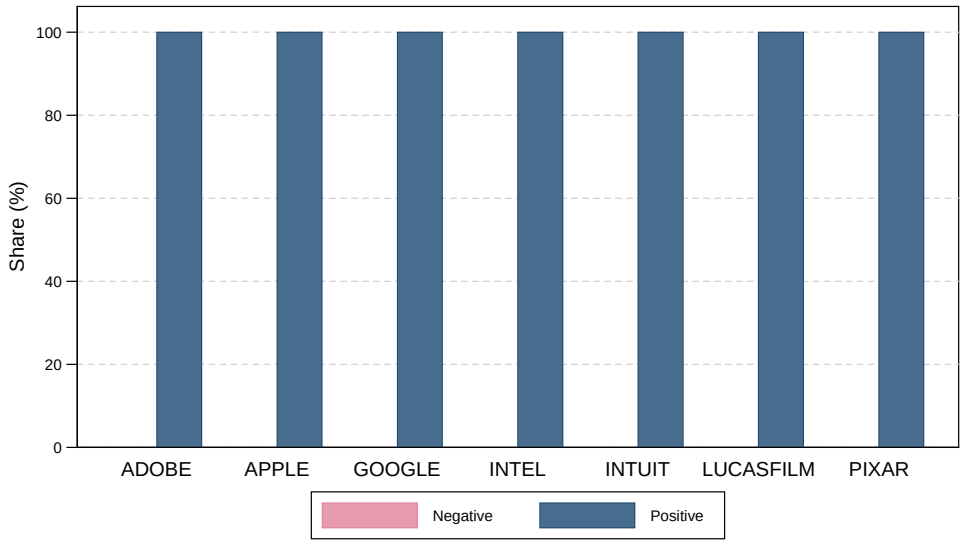
Figure 9: Large Share of Change Correlations are Positive



Source: Defendant Employee Compensation Data; Correlation Analysis

Note: Distribution of growth in avg compensation correlation weighted by class-period employee years

Figure 10: Large Share of Level Correlations are Positive



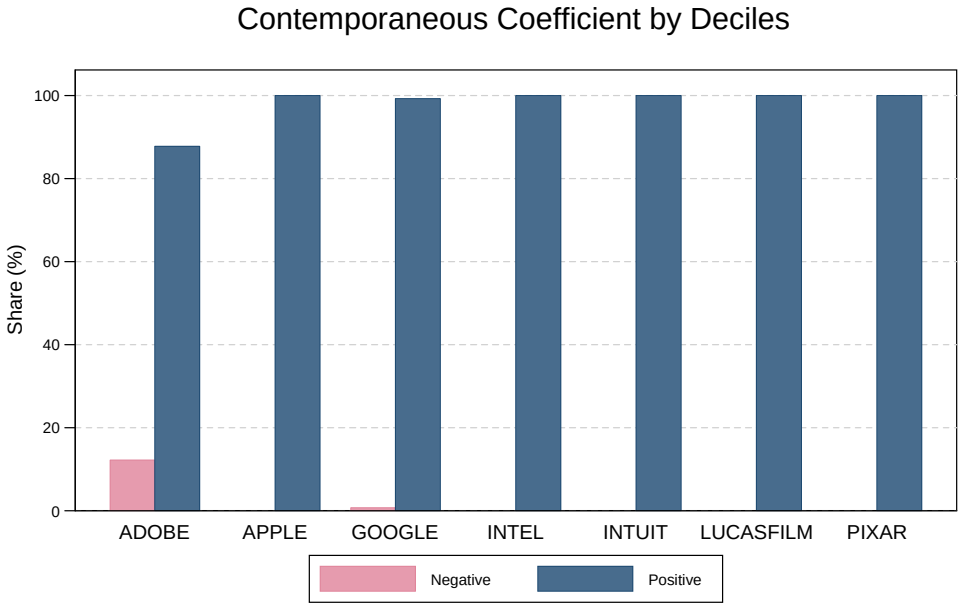
Source: Defendant Employee Compensation Data; Correlation Analysis

Note: Distribution of log avg compensation correlation weighted by class-period employee years

B. Decile Based Multiple Regression Results

45. Multiple regressions have also been estimated with these decile data. As summarized in Figure 11 and Figure 12, below, positive sharing effects—both contemporaneous and lagged—are the rule.

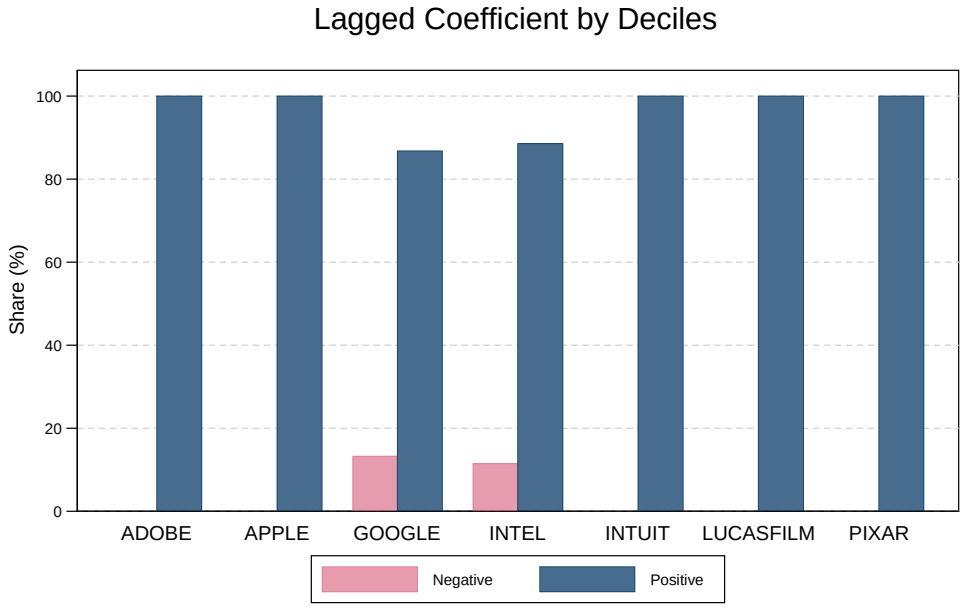
Figure 11: Large Share of Contemporaneous Coefficients are Positive



Source: Defendant Employee Compensation Data; Regression Analysis

Note: Distribution of estimated contemporaneous coefficient weighted by class-period employee years

Figure 12: Large Share of Lagged Coefficients are Positive



Source: Defendant Employee Compensation Data; Regression Analysis

Note: Distribution of estimated lagged coefficient weighted by class-period employee years

46. The almost always positive coefficients on the "corrective" variable in Figure 12 indicate that if the title compensation of a decile departs from its normal relationship with the class, then corrective action is taken to either raise or lower compensation in the decile. The cold-calling conspiracy that would have direct impact suppressing wages in some titles would have some effect on the class-wide averages which in turn would suppress compensation in all or almost all of the titles in the class.

47. Figure 11 and Figure 12 contain a few instances of negative estimates. There are several important things to note. First, every group has a positive sharing effect in either the contemporaneous relationship or the lagged relationship. Second those that are negative are not statistically significant. Third, these occur in the context of evidence of positive sharing relationships for almost every group. Many of these are statistically significant. In sum, this analysis provides support for internal relationships across all these groups that would tend to make impact common to each.

48. Here I want to issue another warning about misinterpretation of negative coefficients. It is important to realize that these coefficients can be affected by the changing composition of the workforce within each title.[9] For instance, adding a number of junior workers might bring down the title's average compensation (or vice versa) for reasons unrelated to the question of whether workers share broadly in things such as the gains of the company and the impact of the unlawful agreements. Idiosyncratic variability of individual characteristics within a title is going to be a bigger problem for titles with just a few employees and for titles that experience large changes[10] in their headcounts.

49. Taking into account the limitations of these data, I find no compelling reason in this analysis to exclude any of the titles from the Technical Class.

VI. Additional Exploration of Adobe Correlations

50. To test this opinion I have closely examined the correlation outputs for the Adobe dataset as set forth below. They confirm my view. I have similarly examined the data of the other defendants, and find nothing in that data to contradict this conclusion.

1. Adobe Correlation Results

51. The numerical correlations reported in compare the movement of real compensation for each title in the Technical Class with the movement of the compensation of the Technical Class overall, but excluding the selected title. A high positive correlation means that compensation of a title moves in a way that is similar to compensation in the rest of the Technical Class, thus supporting the conclusion that the title and the class have "coordinated" compensation levels, a fact which is consistent with sharing of gains and broad impact of the anti-cold-

[9] I previously demonstrated with the Common Factors Analysis that compensation at the individual level in any year depends on the title but also depends on measured individual characteristics including age. This is statistical confirmation that at least some individual characteristics matter, and this raises the possibility that changes in the individual characteristics within a title can cause changes in title compensation that can mask the firm-wide common component.

[10] Though a stable headcount can come from equal numbers of departures and new arrivals.

calling conspiracy whether it directly affects the title under study or the rest of the Technical Class.

52. Titles are included in the table if they are populated in 6 or more years. The correlations based on 5 or fewer observations are often statistically insignificant. The table is sorted first by the number of years the title was populated, from 11 to 6, and then by the correlation of the title with the Technical Class overall. Titles with the strongest statistical correlation with the Technical Class at Adobe are shaded in green. Titles with the weakest statistical correlation with the Technical Class at Adobe are shaded in yellow.

53. The first column of numbers in Exhibit 1 has the first year of data for each title. This is important since the early years from 2001 to 2003 had a sharp decline in Technical Class compensation for Adobe, as illustrated in Figure 13 and these early years thus are an important test bed for identifying which titles moved together. It would not be surprising to find statistically weaker results if these years are not included.

Figure 13

Adobe Technical Class Average Total Compensation

Source: Defendant Employee Compensation Data

Note: Inflation-adjusted average compensation with 2011 as base year

54. The second column reports the number of years during which the title was populated. This is also important since the statistical accuracy of the estimate of correlation depends on the number of observations. For that reason, I have truncated this table at the number of years equal to 6 or more since the cases with 5 or fewer years populated are estimated with greater statistical error.

55. The third column measures the number of employee-years.

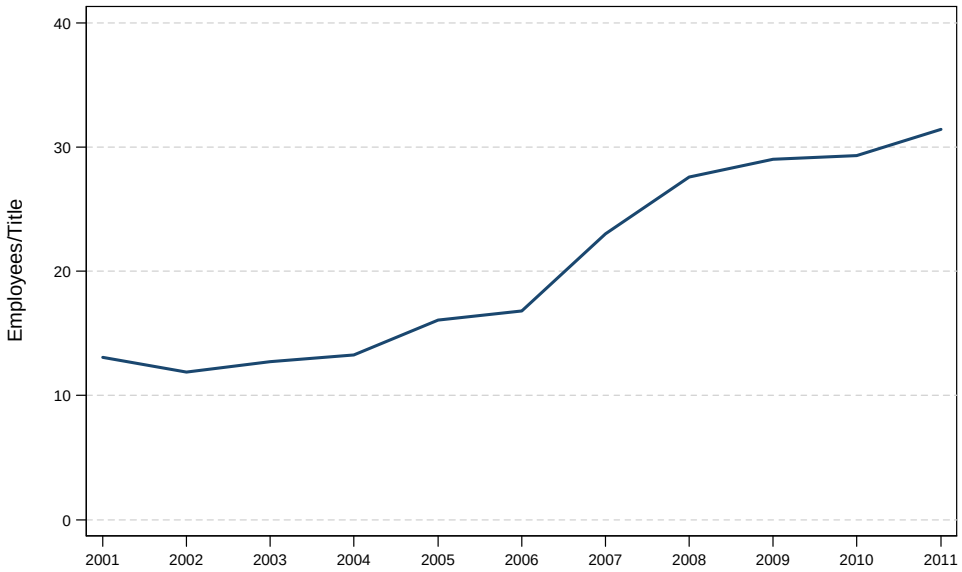
2. Headcount Matters for Interpreting Correlations

56. It is my view that compensation is influenced by the title structure, but not fully determined by the title structure. Variables like age, experience, company tenure and personal characteristics are likely to have an impact on compensation, and consequently some of the change in compensation at the title level comes from changes in the distribution of employee characteristics as employees come and go. Titles that have just a few employees may have unusual employee characteristics, and titles that lose or gain a large fraction of employees may have variability in average compensation that is substantially influenced by variability of these characteristics, which masks a close connection with the Technical Class overall.

57. The Technical Class overall has experienced a rising headcount, as illustrated in Figure 14. Titles with movement in headcounts similar to the Technical Class may experience similar movements in employee characteristics, while titles that are losing workers or gaining workers much more rapidly than the Technical Class overall may have average compensation histories different from the Technical Class, not because there is no sharing, but because the group of employees in the title is changing enough to mask the sharing.

Figure 14

Adobe Technical Class Average Headcount per Title



Source: Defendant Employee Compensation Data

3. Correlations

58. As described above, there are two types of correlations which are relevant for determining if the movements of the two series are similar. The first column of correlations (Section 2) in Exhibit 1 compares the logarithm of average total real compensation in the title and the logarithm of average real total compensation of the rest of the Technical Class. The third column of Section 2 compares the *change* in the logarithm of average real total compensation of the title with the Technical Class (excluding the title).

59. The corresponding t-statistics for these correlations are reported immediately following each correlation and the statistically significant correlations with t-statistics greater than two are shaded. The table is sorted first by the number of years in which the title is populated and second by the correlation between the log levels.

60. The statistically most significant correlations with the shaded t-statistics come from the longest time series with all eleven years of data populated. That is a

feature of any statistical exercise – the longer is the time series the more statistically significant are the findings.

61. There are no negative correlations for the 41 titles with all eleven years populated. These positive correlations are statistically larger than zero (statistically significant) in 39 out of the 41 cases.

4. Outliers

62. To fully understand these correlations, and the significance (or not) of the anomalies, it may be helpful to look at some data displays. Figure 15 and Figure 16 have the average real compensation for ten Adobe titles and for the Adobe employees in the Technical Class overall. Figure 15 illustrates the five titles with eleven years of data that are most highly correlated with the Technical Class overall, and Figure 16 has the least correlated titles. All these titles move together. The title with the lowest correlation is TECHNICAL_WRITER_2 which is different, but not dramatically so.

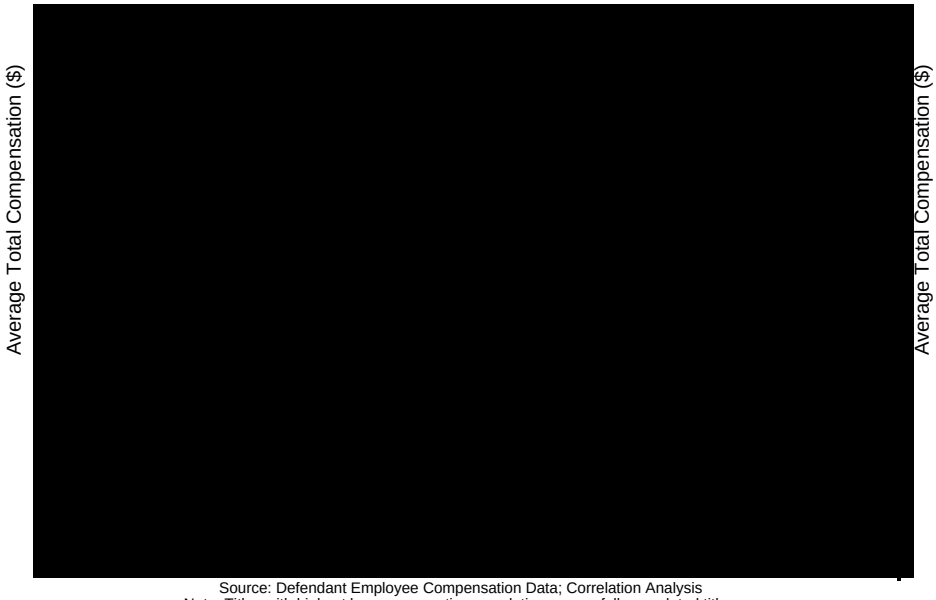
Figure 15: Selected Adobe Titles with a Full 11 years of Data

Most Correlated Titles Average Total Compensation

Source: Defendant Employee Compensation Data; Correlation Analysis
Note: Titles with highest log compensation correlation among fully populated titles
Inflation-adjusted average total compensation with 2011 as base year

Figure 16

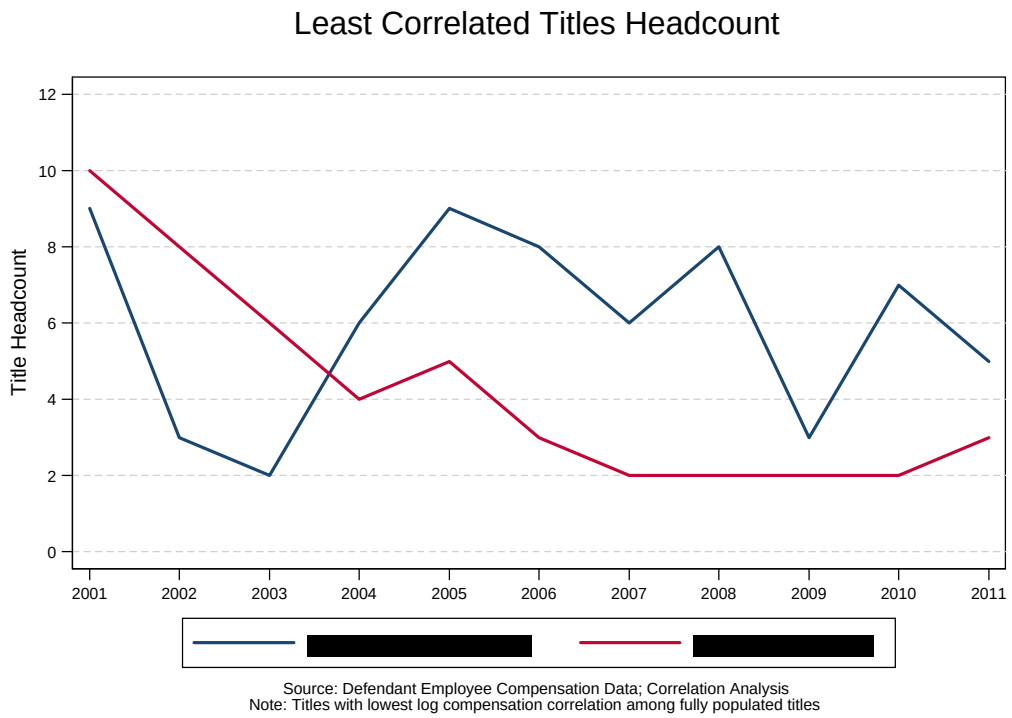
Least Correlated Titles Average Total Compensation



Source: Defendant Employee Compensation Data; Correlation Analysis
Note: Titles with highest log compensation correlation among fully populated titles
Inflation-adjusted average total compensation with 2011 as base year

63. However, as noted above, when headcounts change substantially, employee characteristics may change substantially too. The headcounts for the two titles with the lowest correlation are illustrated in Figure 17. The headcount for [redacted], is very volatile with a standard deviation of the percent change equal to 72 percent compared with the Technical Class benchmark of 11 percent. The [redacted] title is basically withering away, with an average annual percent increase of –12 percent compared with the Technical Class benchmark of +5 percent.

Figure 17: Headcounts: Least Correlated Titles

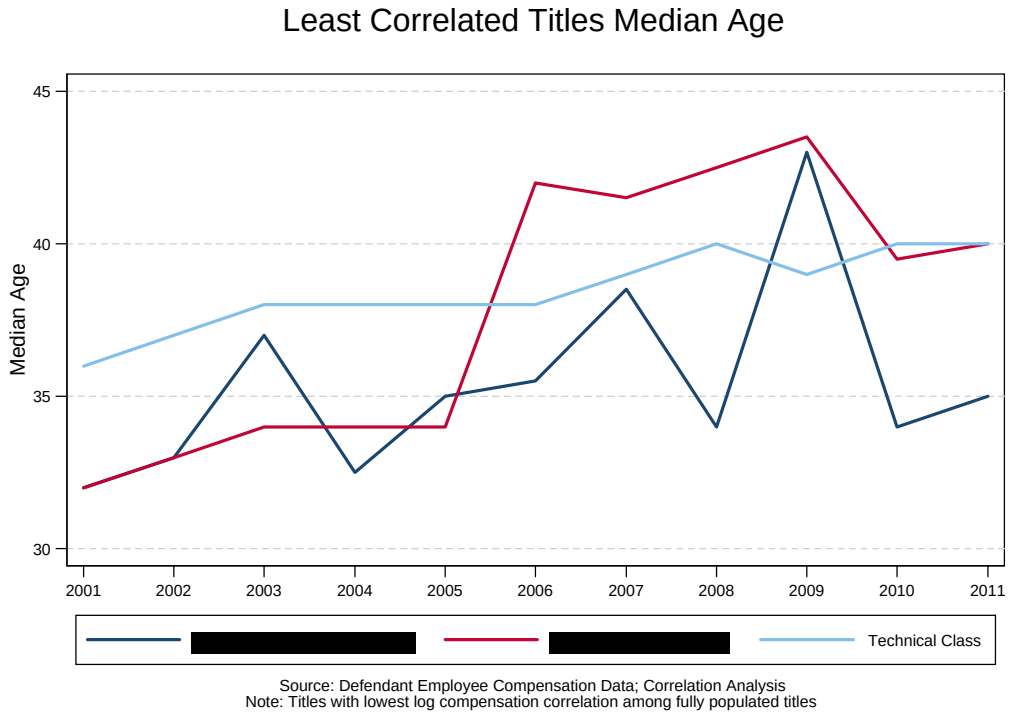


Source: Defendant Employee Compensation Data; Correlation Analysis
Note: Titles with lowest log compensation correlation among fully populated titles

64. The variability in the headcounts for these two titles is not just a hypothetical problem. It has affected substantially the median ages for these titles which are contrasted with the median age of the Technical Class overall in Figure 18. In contrast to the smooth elevation of the median age of the class, the median age of [redacted] has a big jump upward in 2006, and the median age of [redacted] is highly volatile. These facts surely contribute to the apparent disconnect between compensation in these titles and compensation in the Technical Class overall. And, in any event, these results

offer no reason to question my conclusion that Adobe exhibits a somewhat rigid pay structure that applied to all of its salaried employees, including those in these titles. I offer these two examples simply to illustrate the point that the presence of a few outlier titles in the analyses does not challenge our basic conclusions about how these companies pay their employees, which are also supported by economic theory and the evidentiary. I have not seen any evidence, let alone convincing evidence, that any of these titles would not have been harmed by the anti-competitive behavior I have studied.

Figure 18: Median ages: Least Correlated Titles



Source: Defendant Employee Compensation Data; Correlation Analysis
Note: Titles with lowest log compensation correlation among fully populated titles

VII. Internal Versus External Forces

65. The regression analysis reported above indicates that the internal sharing effects are generally more detectable than either revenue sharing or the external market forces. I expand on this finding in this section with an examination of the average real compensation for the Technical Class employees and the non-Technical Class employees of each of the defendants. I show here that there is generally more correlation within firms between these two groups, than between

firms for either group. Thus again I observe that the internal sharing forces are very evident while the external market forces are more difficult to detect.

66. Figure 19 below illustrates for each defendant the average total compensation for the Technical Class employees (RD) and for the non-Technical Class employees (NRD). For most defendants these two subgroups have total compensation that closely tracks one another. It should also be evident that average total compensation is generally much more similar within each firm than between firms. In other words, the internal sharing forces dominate and keep the compensation of the Technical Class employees and the non-Technical Class employees closely aligned.

67. This visual observation is confirmed numerically by the computation of the correlations over time of the change in logarithms of the average total real compensation between these fourteen groups of employees, reported in Table 1. Correlations in excess of 0.9 are shaded. The boxes down the diagonal contain the within firm correlations between RD and NRD. Correlations outside these boxes refer to comparisons between firms. Four out of five of the shaded correlations are in these boxes, and in addition Google has an internal correlation of 0.86. Furthermore, the within firm correlation is the largest correlation in every row and column except for Lucasfilm. Lucasfilm has a very short time series with very little variability in the percent change in compensation, making it hard to estimate correlation . The Pixar data are contaminated by very large bonuses for producers and directors in 2002 and 2006.

68. Table 2 has the levels correlations that capture the longer term co-movements of the compensation series. These confirm the importance of the internal forces compared with the external forces. forces for all but Lucasfilm, in the sense that the within firm correlation is the largest correlation in every row and column except for Lucasfilm. Lucasfilm and Intel appear to move together only because the Lucasfilm data is confined to a brief period of stable growth of compensation at both firms.

Figure 19: Defendant RD vs. NRD Average Total Compensation

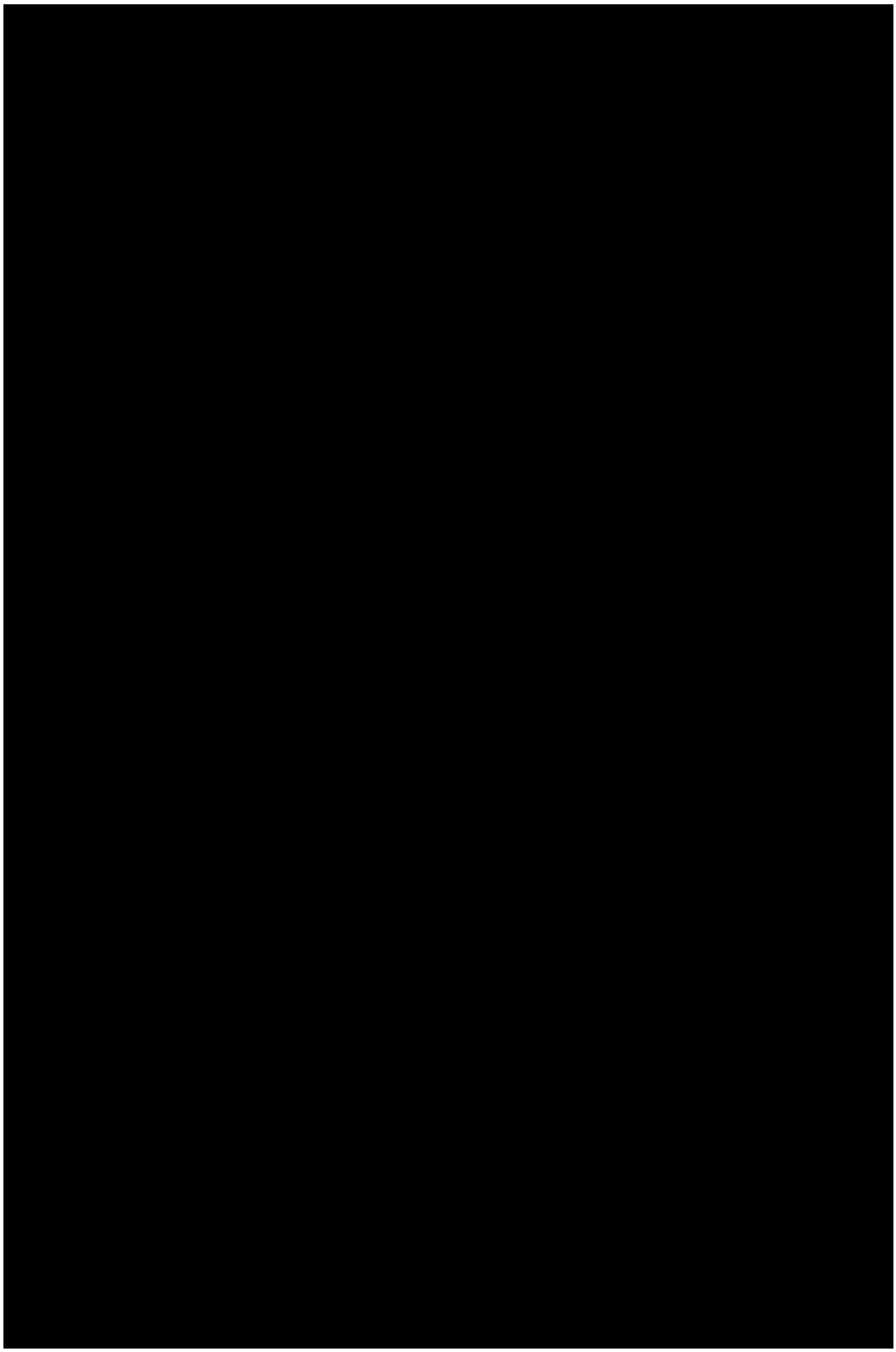


Table 1

Correlations of Changes in Defendants' Average Total Compensation 2001-2011

		Adobe		Apple		Google		Intel		Intuit		Lucasfilm		Pixar	
		NRD	RD	NRD	RD	NRD	RD	NRD	RD	NRD	RD	NRD	RD	NRD	RD
Adobe	NRD	1.00	0.94	0.66	0.56	0.17	-0.16	0.47	0.60	0.63	0.60	0.19	-0.62	-0.53	-0.53
	RD	0.94	1.00	0.64	0.65	0.13	-0.24	0.34	0.45	0.53	0.51	-0.12	-0.67	-0.51	-0.37
Apple	NRD	0.66	0.64	1.00	0.93	0.48	0.17	0.02	0.16	0.85	0.73	-0.08	-0.87	-0.56	-0.16
	RD	0.56	0.65	0.93	1.00	0.42	0.07	-0.12	0.00	0.77	0.63	-0.11	-0.83	-0.45	0.05
Google	NRD	0.17	0.13	0.48	0.42	1.00	0.86	-0.51	-0.39	0.20	0.17	0.49	-0.89	-0.62	0.21
	RD	-0.16	-0.24	0.17	0.07	0.86	1.00	-0.53	-0.50	-0.09	-0.06	0.68	-0.83	-0.50	0.19
Intel	NRD	0.47	0.34	0.02	-0.12	-0.51	-0.53	1.00	0.97	0.31	0.30	-0.01	0.92	0.00	-0.89
	RD	0.60	0.45	0.16	0.00	-0.39	-0.50	0.97	1.00	0.38	0.33	0.23	0.70	-0.03	-0.89
Intuit	NRD	0.63	0.53	0.85	0.77	0.20	-0.09	0.31	0.38	1.00	0.91	-0.15	-0.17	-0.43	-0.28
	RD	0.60	0.51	0.73	0.63	0.17	-0.06	0.30	0.33	0.91	1.00	-0.51	0.55	-0.63	-0.34
Lucasfilm	NRD	0.19	-0.12	-0.08	-0.11	0.49	0.68	-0.01	0.23	-0.15	-0.51	1.00	-0.24	0.03	-0.38
	RD	-0.62	-0.67	-0.87	-0.83	-0.89	-0.83	0.92	0.70	-0.17	0.55	-0.24	1.00	0.58	-0.29
Pixar	NRD	-0.53	-0.51	-0.56	-0.45	-0.62	-0.50	0.00	-0.03	-0.43	-0.63	0.03	0.58	1.00	0.29
	RD	-0.53	-0.37	-0.16	0.05	0.21	0.19	-0.89	-0.89	-0.28	-0.34	-0.38	-0.29	0.29	1.00

Note: Values above 0 9 shaded

Source: Defendants' employee compensation data

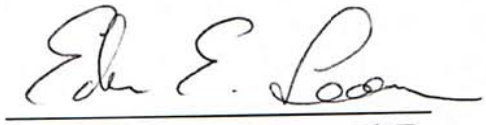
Table 2

Correlations of Defendants' Average Total Compensation 2001-2011

		Adobe		Apple		Google		Intel		Intuit		Lucasfilm		Pixar	
		NRD	RD	NRD	RD	NRD	RD	NRD	RD	NRD	RD	NRD	RD	NRD	RD
Adobe	NRD	1.00	0.88	-0.17	-0.17	-0.43	-0.73	0.18	0.58	0.50	0.41	0.15	-0.04	-0.33	-0.38
	RD	0.88	1.00	0.24	0.27	-0.05	-0.63	0.47	0.72	0.69	0.61	0.40	0.32	-0.48	-0.51
Apple	NRD	-0.17	0.24	1.00	0.99	0.91	0.38	0.65	0.33	0.64	0.68	0.74	0.58	-0.48	-0.39
	RD	-0.17	0.27	0.99	1.00	0.90	0.33	0.69	0.37	0.64	0.66	0.83	0.72	-0.46	-0.40
Google	NRD	-0.43	-0.05	0.91	0.90	1.00	0.67	0.53	0.13	0.36	0.44	0.81	0.59	-0.46	-0.28
	RD	-0.73	-0.63	0.38	0.33	0.67	1.00	-0.05	-0.44	-0.20	-0.08	0.47	0.04	-0.22	0.12
Intel	NRD	0.18	0.47	0.65	0.69	0.53	-0.05	1.00	0.87	0.64	0.66	0.93	0.98	-0.54	-0.86
	RD	0.58	0.72	0.33	0.37	0.13	-0.44	0.87	1.00	0.65	0.62	0.91	0.96	-0.48	-0.90
Intuit	NRD	0.50	0.69	0.64	0.64	0.36	-0.20	0.64	0.65	1.00	0.94	0.63	0.54	-0.55	-0.54
	RD	0.41	0.61	0.68	0.66	0.44	-0.08	0.66	0.62	0.94	1.00	0.78	0.91	-0.72	-0.62
Lucasfilm	NRD	0.15	0.40	0.74	0.83	0.81	0.47	0.93	0.91	0.63	0.78	1.00	0.88	-0.63	-0.83
	RD	-0.04	0.32	0.58	0.72	0.59	0.04	0.98	0.96	0.54	0.91	0.88	1.00	-0.62	-0.86
Pixar	NRD	-0.33	-0.48	-0.48	-0.46	-0.46	-0.22	-0.54	-0.48	-0.55	-0.72	-0.63	-0.62	1.00	0.65
	RD	-0.38	-0.51	-0.39	-0.40	-0.28	0.12	-0.86	-0.90	-0.54	-0.62	-0.83	-0.86	0.65	1.00

Note: Values above 0 9 shaded

Source: Defendants' employee compensation data



Edward E. Leamer, Ph.D.

Exhibit 1
Adobe

Job Title	Section 1						Section 2				Section 3				Section 4				Section 5		Section 6	
	First	Years	Total				Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect			
	Year	of Data	Emp-Years	Avg Emp	dlog Avg	dlog Std Dev	Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	Obs.	r2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
[redacted]	2001	11	170	15	0.27	0.34	0.90	6.07	0.89	5.55	1.18	1.04	0.12	0.02	5.15	6.71	1.77	0.07	2.22	8.15	10	0.98
	2001	11	311	28	0.05	0.19	0.89	5.89	0.78	3.55	1.07	1.18	-0.09	-0.31	0.67	1.38	-0.25	-0.25	2.25	1.66	10	0.74
	2001	11	371	34	0.11	0.16	0.89	5.73	0.79	3.59	0.67	1.33	-0.12	-0.34	0.66	1.95	-0.45	-0.36	2.01	1.99	10	0.81
	2001	11	29	3	0.16	0.65	0.87	5.37	0.78	3.56	2.67	1.08	-0.33	-0.48	1.49	1.80	-0.80	-0.32	3.75	2.24	10	0.79
	2001	11	82	7	0.10	0.25	0.85	4.87	0.72	2.97	0.89	1.09	-0.46	0.58	0.65	1.99	-1.23	0.39	1.97	1.39	10	0.77
	2001	11	108	10	-0.03	0.40	0.84	4.73	0.82	4.08	0.93	0.88	0.04	0.51	2.43	3.32	0.37	1.38	1.81	3.34	10	0.94
	2001	11	96	9	0.12	0.37	0.84	4.65	0.85	4.56	0.80	0.59	0.05	0.84	1.93	2.68	0.45	1.89	1.38	2.66	10	0.95
	2001	11	250	23	0.04	0.16	0.84	4.60	0.85	4.47	1.28	0.97	0.08	0.19	2.60	3.59	0.47	0.37	2.25	3.83	10	0.93
	2001	11	559	51	0.11	0.20	0.83	4.53	0.88	5.31	0.94	0.80	0.21	-0.04	2.27	2.28	1.45	-0.08	1.74	3.24	10	0.92
	2001	11	93	8	0.11	0.26	0.81	4.19	0.67	2.54	3.21	0.89	-0.24	-1.55	1.03	0.75	-0.30	-0.62	4.10	1.49	10	0.63
	2001	11	14	1	0.00	0.45	0.80	3.97	0.63	2.29	2.50	0.06	0.51	-0.17	0.50	0.04	0.40	-0.04	2.57	0.56	10	0.57
	2001	11	152	14	0.28	0.15	0.78	3.74	0.72	2.96	0.54	0.65	0.13	0.54	0.98	1.60	0.89	1.07	1.18	1.43	10	0.81
	2001	11	202	18	0.06	0.25	0.78	3.74	0.70	2.78	0.68	1.24	0.21	0.34	1.30	4.27	1.40	0.67	1.91	3.24	10	0.92
	2001	11	550	50	0.06	0.18	0.78	3.70	0.95	8.29	0.99	0.15	0.06	0.43	2.87	0.54	0.47	0.94	1.14	2.66	10	0.94
	2001	11	234	21	0.07	0.22	0.78	3.68	0.73	2.98	0.97	1.14	0.12	0.29	1.56	2.19	0.43	0.48	2.11	2.22	10	0.82
	2001	11	273	25	0.17	0.19	0.77	3.60	0.74	3.11	0.34	1.32	0.23	0.33	0.60	2.67	1.59	0.66	1.66	2.77	10	0.86
	2001	11	327	30	0.11	0.14	0.74	3.34	0.82	4.00	0.66	0.40	0.11	0.19	1.39	1.12	0.74	0.38	1.06	1.67	10	0.78
	2001	11	434	39	0.07	0.18	0.74	3.29	0.65	2.39	0.72	1.09	0.21	0.30	1.29	2.84	1.33	0.56	1.82	2.39	10	0.84
	2001	11	196	18	0.13	0.24	0.74	3.27	0.82	4.06	1.23	0.57	0.09	0.02	1.48	1.38	0.29	0.02	1.80	1.87	10	0.78
	2001	11	353	32	-0.06	0.19	0.73	3.23	0.56	1.91	0.81	1.43	0.17	0.44	1.59	4.09	1.21	0.94	2.23	3.21	10	0.87
	2001	11	309	28	0.08	0.23	0.71	3.03	0.61	2.20	0.96	1.13	0.06	0.24	1.27	2.23	0.24	0.34	2.09	1.95	10	0.73
	2001	11	94	9	0.08	0.27	0.71	3.03	0.62	2.25	0.65	1.02	0.11	0.58	0.89	2.65	0.49	0.79	1.68	1.74	10	0.83
	2001	11	2095	190	0.05	0.13	0.70	2.91	0.69	2.68	0.26	0.49	0.12	0.35	0.60	1.35	0.88	0.79	0.75	1.25	10	0.72
	2001	11	514	47	0.08	0.22	0.70	2.90	0.63	2.27	0.71	0.97	0.08	0.45	0.91	2.30	0.29	0.57	1.68	1.66	10	0.77
	2001	11	35	3	0.00	0.32	0.69	2.90	0.53	1.75	0.58	1.09	0.15	-0.15	0.45	2.12	0.47	-0.09	1.67	1.05	10	0.81
	2001	11	215	20	0.07	0.53	0.69	2.88	0.46	1.48	0.35	1.26	-0.07	0.47	0.51	3.49	-0.39	0.69	1.61	1.88	10	0.82
	2001	11	496	45	0.05	0.20	0.67	2.74	0.75	3.18	0.08	0.47	0.14	0.56	0.17	1.29	0.89	0.91	0.56	0.87	10	0.83
	2001	11	466	42	0.06	0.11	0.67	2.74	0.69	2.71	0.27	0.62	0.10	0.27	0.49	1.62	0.59	0.48	0.89	1.33	10	0.71
	2001	11	234	21	0.09	0.33	0.67	2.71	0.77	3.39	0.10	0.27	-0.17	1.23	0.21	1.12	-1.01	2.21	0.38	0.63	10	0.87
	2001	11	1441	131	0.06	0.19	0.65	2.55	0.48	1.56	0.24	0.71	0.11	0.54	0.35	1.51	0.58	0.89	0.94	0.98	10	0.61
	2001	11	302	27	0.00	0.21	0.64	2.49	0.91	6.03	0.62	0.10	-0.17	0.94	2.20	0.67	-1.72	2.57	0.72	2.18	10	0.95
	2001	11	222	20	0.09	0.15	0.63	2.44	0.62	2.22	0.05	0.45	0.11	0.75	0.07	1.04	0.51	0.95	0.50	0.52	10	0.70
	2001	11	975	89	-0.12	0.23	0.63	2.42	0.48	1.55	0.24	0.49	0.00	0.40	0.39	1.05	-0.01	0.71	0.73	0.86	10	0.42
	2001	11	2041	186	0.05	0.20	0.61	2.33	0.57	1.94	0.07	0.43	0.14	0.55	0.14	1.04	0.80	1.04	0.50	0.67	10	0.62
	2001	11	56	5	0.03	0.54	0.61	2.32	0.52	1.70	0.27	1.04	0.08	1.06	0.36	2.96	0.39	1.55	1.30	1.43	10	0.83
	2001	11	2064	188	0.05	0.08	0.61	2.29	0.52	1.71	-0.07	0.44	0.13	0.65	-0.14	1.13	0.82	1.29	0.37	0.52	10	0.66
	2001	11	100	9	0.09	0.31	0.60	2.27	0.61	2.20	1.92	0.91	0.00	-3.12	1.44	1.96	0.00	-2.95	2.83	2.36	10	0.86
	2001	11	1008	92	0.06	0.27	0.59	2.17	0.56	1.91	0.36	0.56	0.26	0.29	0.57	1.18	1.41	0.48	0.91	1.09	10	0.62
	2001	11	41	4	0.00	0.59	0.58	2.11	0.34	1.02	0.41	1.61	0.19	-0.56	0.42	2.35	0.55	-0.42	2.01	1.37	10	0.71
	2001	11	66	6	-0.06	0.72	0.51	1.77	0.37	1.13	-1.62	-0.86	-0.57	1.57	-4.28	-3.06	-4.84	5.82	-2.48	-3.98	10	0.91
	2001	11	47	4	-0.12	0.30	0.09	0.26	0.14	0.40	-1.20	0.28	-0.07	1.62	-1.61	1.16	-0.33	2.25	-0.92	-1.12	10	0.61
	2002	10	36	4	0.10	0.40	0.80	3.72	0.77	3.22	1.91	1.28	-0.39	0.00	1.54	1.76	-1.17	0.00	3.19	2.50	9	0.78
	2002	10	37	4	0.08	0.43	0.14	0.39	-0.59	-1.93	0.12	1.09	0.06	0.40	0.19	2.35	0.43	0.73	1.20	1.25	9	0.76
	2002	10	26	3	0.00	0.48	-0.02	-0.06	0.14	0.37	3.38	0.87	0.35	5.30	1.21	1.33	0.52	1.81	4.25	1.45	9	0.96
	2002	10	330	33	0.20	0.29	-0.13	-0.37	0.08	0.22	-0.35	0.30	0.13	0.64	-1.22	1.84	1.72	1.89	-0.05	-0.13	9	0.83
	2001	9	44	5	-0.30	0.50	0.52	1.59	0.46	1.28	-0.47	0.51	0.04	1.39	-0.42	0.97	0.12	1.19	0.04	0.03	8	0.71
	2001	9	104	12	-0.21	0.48	0.30	0.85	0.37	0.99	-0.36	1.29	0.16	1.66	-0.15	0.67	0.19	0.56	0.93	0.47	8	0.51
	2004	8	94	12	0.30	0.91	0.84	3.82	0.63	1.80	1.70	0.88	-0.61	1.82	5.22	4.89	-6.25	3.47	2.59	6.88	7	0.98
	2001	8	143	18	-0.40	1.08	0.70	2.38	0.68	2.05	1.42	1.60	0.16	0.45	4.02	3.62	1.15	0.85	3.02	7.37	7	0.98
	2001	8	8	1	0.00	0.00	0.62	1.92	-0.36	-0.78	4.15	2.48	-0.14	-0.81	1.02	1.65	-0.13	-0.19	6.63	1.22	6	0.90
	2001	8	93	12	-0.28	1.28	0.56	1.64	0.52	1.37	-0.50	0.43	-0.07	1.14	-0.33	0.71	-0.13	0.66	-0.07	-0.05	7	0.60
	2001	8	88	11	-0.10	1.44	0.38	1.02	0.58	1.58	0.41	2.01	-0.02	2.16	0.60	3.63	-0.07	2.27	2.42	3.81	7	0.93
	2001	8	64	8	-0.43	0.54	0.31	0.80	0.30	0.71	1.40	0.61	0.34	-0.70	0.63	0.51	0.47	-0.28	2.01	1.01	7	0.50
	2004	8	50	6	0.14	0.33	0.28	0.73	0.65	1.89	1.28	0.54	0.27	2.46	4.87	4.48	2.92	5.63	1.82	6.05	7	0.99
	2001	8	32	4	0.20	0.81	0.15	0.36	0.40	0.75												
	2004	8	18	2	0.00	0.61	-0.17	-0.41	0.60	1.66	1.10	0.66	0.04	2.14	1.76	3.36	0.15	2.00	1.76	2.76	7	0.91

Exhibit 1
Adobe

Job Title	Section 1						Section 2				Section 3				Section 4				Section 5		Section 6	
	First Year	Years of Data	Total Emp-Years	Avg Emp	dlog Avg	dlog Std Dev	Level Correlation Coeff	Level Correlation T-Stat	Change Correlation Coeff	Change Correlation T-Stat	Regression Coefficients Contemp	Regression Coefficients Lagged	Regression Coefficients Revenue	Regression Coefficients SJ Emp	Regression T-Stats Contemp	Regression T-Stats Lagged	Regression T-Stats Revenue	Regression T-Stats SJ Emp	Net Effect C + L	Net Effect T-Stat	Obs.	r2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
[redacted]	2005	7	22	3	0.18	0.41	0.76	2.64	-0.15	-0.31	0.14	0.93	-0.38	-0.36	0.11	1.48	-0.68	-0.21	1.07	0.60	6	0.91
	2001	7	42	6	-0.27	0.76	0.57	1.56	0.39	0.84	-3.13	2.20	-0.57	3.68	-2.63	2.79	-1.65	2.92	-0.93	-1.11	6	0.93
	2001	7	88	13	-0.41	0.33	0.53	1.38	0.38	0.82	-3.36	5.49	-1.61	7.47	-4.12	6.77	-4.51	5.53	2.13	10.60	6	1.00
	2001	7	17	2	0.00	0.36	0.48	1.21	0.93	4.88	0.58	0.42	-0.13	0.77	0.54	0.84	-0.54	0.89	1.00	0.71	6	0.95
	2005	7	93	13	0.00	0.27	0.40	0.98	0.97	7.56	1.30	0.10	0.07	0.02	2.06	0.28	0.24	0.03	1.40	1.76	6	0.94
	2005	7	59	8	0.05	0.36	0.08	0.18	0.52	1.21	0.49	0.70	0.24	-0.26	0.34	0.76	0.40	-0.13	1.19	0.61	6	0.73
	2001	6	46	8	0.14	0.21	0.98	10.31	0.90	3.49												
	2001	6	25	4	0.36	0.95	0.97	8.18	0.86	2.98												
	2001	6	19	3	-0.06	0.45	0.96	7.28	0.93	4.41												
	2001	6	87	15	0.03	0.12	0.96	6.72	0.83	2.55												
	2001	6	13	2	-0.28	1.05	0.94	5.50	0.94	4.92												
	2001	6	89	15	0.11	0.43	0.94	5.29	0.82	2.47												
	2001	6	108	18	0.01	0.23	0.93	5.23	0.74	1.90												
	2001	6	20	3	0.00	0.20	0.93	5.11	0.78	2.17												
	2001	6	16	3	-0.06	0.70	0.92	4.77	0.58	1.23												
	2001	6	33	6	-0.08	0.33	0.92	4.62	0.66	1.52												
	2001	6	22	4	0.03	0.74	0.89	3.99	0.94	4.80												
	2001	6	23	4	0.22	0.49	0.89	3.90	0.67	1.54												
	2001	6	35	6	0.09	0.26	0.89	3.87	0.91	3.90												
	2001	6	57	10	0.06	0.53	0.88	3.77	0.47	0.91												
	2001	6	10	2	0.22	0.32	0.88	3.74	0.50	1.00												
	2001	6	24	4	-0.25	1.15	0.88	3.70	0.83	2.11												
	2001	6	21	4	-0.36	0.59	0.88	3.66	0.49	0.97												
	2001	6	92	15	0.19	0.16	0.87	3.60	0.78	2.16												
	2001	6	68	11	0.00	0.21	0.86	3.44	0.66	1.51												
	2001	6	13	2	0.00	0.29	0.86	3.43	0.59	1.28												
	2001	6	27	5	0.42	0.63	0.86	3.38	0.74	1.92												
	2001	6	8	1	0.00	0.49	0.85	3.28	0.93	4.31												
	2001	6	15	3	-0.08	0.34	0.85	3.18	0.27	0.49												
	2001	6	26	4	-0.04	0.41	0.82	2.84	0.76	2.03												
	2006	6	7	1	-0.14	0.31	0.81	2.81	0.85	2.85												
	2001	6	18	3	0.00	0.51	0.67	1.79	0.43	0.82												
	2001	6	105	18	-0.04	0.36	0.66	1.74	0.68	1.59												
	2006	6	27	5	0.14	0.46	0.62	1.57	0.61	1.34												
	2006	6	19	3	-0.08	0.52	0.61	1.55	0.54	1.11												
	2001	6	15	3	-0.14	0.90	0.61	1.54	-0.14	-0.24												
	2001	6	12	2	0.22	0.32	0.57	1.39	0.76	2.05												
	2001	6	15	3	-0.22	0.32	0.57	1.38	0.56	1.17												
	2006	6	19	3	0.28	0.53	0.34	0.72	-0.21	-0.38												
	2004	6	6	1	0.00	0.00	0.13	0.26	0.28	0.50												
	2001	6	15	3	0.06	0.73	0.10	0.20	0.62	1.36												
	2001	6	11	2	0.08	0.52	0.03	0.05	0.16	0.28												
	2002	6	115	19	0.40	0.29	-0.03	-0.06	-0.72	-1.47												
	2002	6	11	2	0.14	0.31	-0.17	-0.34	0.11	0.20												
	2006	6	24	4	0.37	0.73	-0.45	-1.00	-0.93	-4.22												

Exhibit 2
Apple

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years	Total	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		
	of Data	Emp-Years	Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
[redacted]	11	294	0.98	13.53	0.74	3.11	0.80	0.04	0.34	-0.06	1.64	0.05	0.81	-0.13	0.84	0.76	0.71
	11	501	0.98	13.42	0.87	4.91	2.46	1.09	-0.70	-0.67	5.33	1.71	-1.82	-1.18	3.56	4.85	0.92
	11	229	0.98	13.33	0.65	2.41	1.15	0.97	0.09	-0.08	2.58	1.52	0.26	-0.19	2.12	2.15	0.73
	11	169	0.97	12.72	0.70	2.79	1.29	1.49	-0.57	0.28	2.17	1.67	-1.00	0.46	2.78	2.20	0.72
	11	352	0.95	9.16	0.71	2.82	0.92	-0.22	0.76	0.16	1.56	-0.39	1.55	0.26	0.71	0.72	0.78
	11	189	0.93	7.38	0.84	4.39	1.68	0.36	0.20	0.87	1.81	0.38	0.26	0.87	2.04	1.39	0.82
	11	428	0.91	6.72	0.65	2.45	0.51	4.63	-2.48	1.62	0.53	2.82	-2.28	1.57	5.14	2.93	0.82
	11	156	0.88	5.54	0.39	1.21	0.71	0.25	0.28	-0.62	0.95	0.38	0.40	-0.67	0.96	0.77	0.29
	11	118	0.68	2.82	0.36	1.09	0.58	0.17	-0.11	-0.23	0.86	0.31	-0.16	-0.24	0.75	0.70	0.16
	11	686	-0.49	-1.69	0.43	1.33	0.66	0.47	-0.15	-0.49	0.68	0.60	-0.18	-0.40	1.13	0.73	0.52
	11	58	-0.50	-1.71	0.07	0.20	0.03	-0.11	0.21	-0.27	0.05	-0.28	0.49	-0.47	-0.09	-0.11	0.10
	10	82	-0.67	-2.52	0.03	0.08	-0.38	0.08	0.18	0.01	-0.39	0.10	0.22	0.01	-0.30	-0.19	0.34
	10	184	-0.81	-3.84	-0.25	-0.68	-0.17	0.08	0.18	-0.91	-0.20	0.11	0.24	-0.81	-0.09	-0.07	0.40
	10	110	-0.81	-3.93	0.71	2.64	0.69	0.07	-0.04	-0.53	2.98	0.36	-0.18	-1.86	0.76	2.06	0.75
	10	66	-0.89	-5.57	0.04	0.11	-0.14	-0.06	0.06	0.20	-1.03	-0.53	0.47	1.12	-0.20	-0.92	0.36
	9	116	-0.85	-4.33	-0.55	-1.59	-0.43	0.03	0.14	-0.95	-1.37	0.14	0.54	-1.36	-0.39	-0.79	0.83
	8	44	0.98	11.69	0.59	1.27	1.84	3.27	-2.40	1.69							
	8	35	0.97	9.97	0.78	2.48	0.30	0.21	1.02	-0.21	1.13	0.37	3.49	-0.93	0.50	0.73	0.99
	8	19	0.76	2.89	-0.62	-1.78	-0.16	0.16	0.02	-0.78	-0.78	0.97	0.13	-1.91	0.00	-0.01	0.86
	8	52	-0.82	-3.57	0.02	0.05	0.14	0.08	-0.13	-0.07	0.50	0.28	-0.51	-0.36	0.22	0.40	0.57
	8	13	-0.96	-7.90	0.24	0.55	0.09	0.05	-0.03	-0.22	0.84	0.50	-0.27	-0.69	0.14	0.78	0.51
	7	71	0.99	22.21	0.95	5.95	0.54	-0.46	0.07	0.06	1.39	-0.22	0.15	0.04	0.08	0.03	0.94
	7	193	0.99	20.45	0.95	6.20	1.49	1.49	-0.41	0.82	12.36	3.86	-2.99	1.89	2.98	6.80	1.00
	7	626	0.99	16.77	0.94	5.77	1.41	1.40	-0.29	0.07	30.92	4.57	-3.71	0.27	2.82	8.34	1.00
	7	184	0.99	16.70	0.96	6.91	1.16	1.48	-0.31	0.23	3.69	0.99	-0.69	0.27	2.64	1.81	0.97
	7	2566	0.99	14.96	0.92	4.55	0.88	0.60	0.16	-0.65	10.23	3.85	1.64	-3.23	1.48	7.27	0.99
	7	29	0.99	13.76	0.81	2.81	0.24	-0.38	0.08	0.22	0.48	-0.29	0.14	0.12	-0.14	-0.08	0.80
	7	253	0.98	12.12	0.92	4.72	0.76	1.16	0.20	-0.64	1.85	1.01	0.73	-0.66	1.92	1.84	0.95
	7	130	0.98	10.75	0.89	3.94	-0.47	5.06	1.65	-5.63	-0.64	1.93	1.97	-1.78	4.59	2.36	0.97
	7	447	0.98	10.68	0.95	6.15	1.48	0.65	0.02	-0.45	2.89	0.47	0.04	-0.35	2.12	1.64	0.96
	7	244	0.98	10.66	0.88	3.63	-0.18	-4.02	1.70	-0.93	-0.73	-3.21	3.80	-7.34	-4.20	-2.81	1.00
	7	125	0.98	9.93	0.86	3.39	0.99	1.14	0.05	0.09	4.26	3.10	0.20	0.19	2.14	5.47	0.98
	7	1364	0.98	9.91	0.93	4.96	0.85	0.41	0.34	-1.08	5.64	1.91	2.09	-2.89	1.26	4.61	0.99
	7	54	0.97	9.77	0.81	2.81	1.59	2.35	-1.09	2.20	5.11	4.37	-4.08	2.80	3.94	6.55	0.98
	7	236	0.97	9.58	0.97	7.42	0.99	0.57	0.28	-0.18	2.55	1.16	0.76	-0.24	1.56	3.63	0.97
	7	475	0.97	9.33	0.84	3.04	0.55	0.80	0.42	-1.16	2.01	1.71	1.67	-1.34	1.35	2.55	0.95
	7	1304	0.97	9.17	0.81	2.81	0.66	0.37	0.03	-0.87	9.39	3.50	0.50	-5.68	1.03	6.50	0.99
	7	110	0.97	8.72	0.95	6.06	1.93	1.07	-0.23	0.24	108.02	31.38	-14.63	4.22	3.00	79.73	1.00
	7	902	0.97	8.62	0.82	2.84	0.83	0.68	0.49	-1.09	13.99	9.36	7.98	-7.66	1.52	14.05	1.00
	7	371	0.97	8.61	0.94	5.61	0.64	-0.22	0.04	-0.32	3.23	-0.70	0.13	-0.45	0.42	1.05	0.96
	7	68	0.97	8.25	0.96	6.93	1.64	0.38	0.00	-0.12	1.64	0.20	0.00	-0.08	2.03	1.35	0.93
	7	61	0.96	8.15	0.59	1.48	0.73	0.90	0.29	-1.36	2.84	2.23	1.66	-2.62	1.63	2.69	0.95
	7	26	0.96	8.01	0.86	3.40	3.03	1.10	-0.85	-1.59	8.22	0.94	-1.26	-0.56	4.13	3.04	0.99
	7	549	0.96	7.91	0.94	5.57	1.06	-0.90	0.48	-0.87	21.14	-4.50	9.58	-8.12	0.16	0.82	1.00
	7	127	0.96	7.88	0.93	5.24	2.07	1.20	-0.26	0.97	3.58	1.36	-0.58	0.57	3.27	3.17	0.97
	7	118	0.96	7.80	0.69	1.90	1.62	1.95	-0.25	1.40	4.18	3.14	-0.85	1.50	3.57	3.90	0.97
	7	682	0.96	7.79	0.88	3.70	1.09	0.81	0.48	-0.70	5.58	2.55	2.39	-1.62	1.90	4.53	0.98
	7	167	0.96	7.75	0.91	4.31	1.32	0.59	0.02	0.75	1.37	0.39	0.03	0.46	1.92	1.38	0.91
	7	146	0.96	7.71	0.62	1.59	0.74	0.99	0.05	-0.79	3.63	3.13	0.34	-1.83	1.72	3.72	0.96
	7	29	0.96	7.63	0.56	1.36	1.70	2.20	-0.62	1.55	2.79	2.35	-1.22	1.13	3.91	2.72	0.94
	7	121	0.96	7.62	0.87	3.46	-0.61	5.97	-1.48	-0.02	-1.34	5.40	-4.59	-0.04	5.36	7.02	0.99
	7	63	0.96	7.52	0.90	4.06	2.37	2.06	-0.91	2.63	16.54	8.37	-8.14	4.46	4.43	16.33	1.00
	7	1363	0.96	7.33	0.91	4.37	0.94	0.75	0.28	-1.10	1.79	0.89	0.73	-1.05	1.69	1.98	0.94
	7	16	0.95	7.10	0.73	2.15	2.74	8.01	-4.63	8.30	9.55	7.14	-6.76	4.97	10.75	8.46	0.99

Exhibit 2
Apple

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years	Total	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		
	of Data	Emp-Years	Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
[redacted]	7	17	0.95	7.08	0.71	2.01	1.88	6.66	-3.36	7.09	7.10	9.22	-8.26	6.61	8.54	10.88	1.00
	7	127	0.95	6.94	0.52	1.21	0.56	0.19	-0.28	1.66	15.61	2.26	-7.87	16.05	0.75	7.07	1.00
	7	142	0.95	6.80	0.83	2.99	-0.30	3.49	-0.40	-0.56	-0.28	2.08	-0.91	-0.41	3.19	2.94	0.95
	7	63	0.95	6.73	0.69	1.92	1.09	2.55	-0.84	2.00	2.49	4.60	-2.54	2.18	3.64	5.17	0.98
	7	45	0.95	6.73	0.99	12.42	2.37	-0.57	0.11	-0.28	3.89	-0.73	0.43	-0.38	1.80	3.15	0.98
	7	98	0.95	6.52	0.84	3.11	0.42	-0.03	0.15	-0.86	2.29	-0.16	0.60	-1.47	0.39	1.18	0.93
	7	70	0.94	6.46	0.88	3.72	1.03	3.36	0.26	1.34	1.02	0.65	0.33	0.29	4.39	1.02	0.95
	7	182	0.94	6.42	0.96	7.04	1.85	0.66	-0.02	-0.43	20.57	4.80	-0.28	-1.92	2.51	19.20	1.00
	7	2915	0.94	6.33	0.60	1.52	0.75	0.73	-0.18	-0.36	3.05	2.18	-0.96	-0.70	1.48	2.83	0.92
	7	134	0.94	6.30	0.66	1.76	0.94	1.02	-0.16	0.07	8.01	7.07	-1.52	0.25	1.97	9.04	0.99
	7	143	0.94	6.27	0.48	1.10	0.38	0.26	0.73	-1.64	0.87	0.46	1.94	-1.39	0.64	0.68	0.84
	7	476	0.94	6.23	0.91	4.31	3.20	-2.66	-1.18	5.55	2.00	-1.31	-1.16	1.44	0.53	0.75	0.96
	7	53	0.94	6.18	0.79	2.54	1.14	0.91	0.12	0.64	3.07	1.95	0.41	0.78	2.05	3.12	0.98
	7	275	0.94	6.09	0.70	1.97	0.82	0.80	0.45	-1.06	2.39	1.55	1.68	-1.39	1.62	2.24	0.97
	7	255	0.93	5.78	0.74	2.21	-0.07	2.18	0.57	-1.09	-0.15	4.59	2.06	-1.39	2.11	4.69	0.98
	7	300	0.93	5.69	0.38	0.82	0.33	0.33	-0.09	-0.42	1.51	1.22	-0.67	-1.12	0.66	1.43	0.82
	7	125	0.93	5.69	0.79	2.56	0.64	1.88	0.06	0.58	5.01	16.56	0.79	2.97	2.52	18.16	1.00
	7	262	0.93	5.65	0.51	1.18	0.99	1.54	-0.46	-0.24	4.29	4.47	-2.58	-0.49	2.53	5.03	0.97
	7	16	0.93	5.63	0.72	2.10	1.20	1.08	-0.14	0.10	2.30	1.36	-0.24	0.08	2.28	2.10	0.97
	7	115	0.93	5.58	0.27	0.57	0.71	0.94	0.29	-1.78	0.41	0.33	0.52	-1.46	1.65	0.36	0.76
	7	33	0.93	5.56	0.55	1.31	1.06	1.69	-0.48	-0.89	11.73	10.86	-6.30	-4.69	2.75	12.46	1.00
	7	16	0.93	5.55	0.47	1.06	2.57	3.07	-1.01	2.89	2.51	2.15	-1.27	1.18	5.64	2.42	0.92
	7	35	0.93	5.46	0.68	1.85	0.43	0.40	0.43	-1.40	0.92	0.30	0.85	-1.10	0.83	0.53	0.92
	7	297	0.92	5.42	0.84	3.04	0.57	1.74	0.21	-0.65	0.73	2.15	0.46	-0.55	2.30	2.76	0.95
	7	57	0.92	5.39	0.72	2.05	0.69	0.70	0.36	-0.74	2.04	2.46	0.95	-0.86	1.39	2.85	0.94
	7	58	0.92	5.35	0.78	2.48	0.81	0.46	0.29	-0.50	3.21	2.06	0.77	-0.78	1.28	3.10	0.94
	7	26	0.92	5.30	0.67	1.80	2.23	2.43	-1.17	-0.57	5.76	2.33	-1.86	-0.37	4.66	3.32	1.00
	7	115	0.92	5.30	0.64	1.68	0.86	0.53	0.05	-1.73	81.85	34.93	6.57	-83.66	1.39	58.99	1.00
	7	103	0.92	5.23	0.35	0.74	0.71	2.91	-1.10	-0.68	1.67	3.08	-2.22	-0.72	3.62	3.03	0.94
	7	35	0.92	5.21	0.59	1.45	0.67	4.66	-1.96	0.59	1.56	5.68	-4.15	0.64	5.33	5.82	0.99
	7	49	0.92	5.14	0.67	1.79	1.20	0.72	0.03	-2.50	2.41	0.57	0.03	-1.91	1.92	1.15	0.98
	7	23	0.92	5.12	0.89	3.94	1.50	-0.38	0.73	-0.15	3.16	-0.60	1.79	-0.15	1.12	1.44	0.98
	7	431	0.91	5.03	-0.24	-0.50	-0.05	0.05	0.05	-0.41	-0.10	0.09	0.19	-0.45	0.01	0.01	0.23
	7	21	0.91	4.94	0.54	1.30	3.18	3.81	-0.09	4.43	4.28	3.52	-0.31	2.38	6.99	3.91	0.96
	7	64	0.91	4.93	0.33	0.71	0.14	0.85	0.65	-1.56	2.39	11.13	11.42	-6.65	0.99	9.56	1.00
	7	56	0.91	4.86	0.93	4.90	3.28	-0.05	-0.48	-3.16	26.16	-0.30	-13.49	-7.06	3.23	35.05	1.00
	7	14	0.91	4.86	-0.40	-0.86	-0.07	-0.01	-0.16	0.43	-1.14	-0.23	-1.50	1.66	-0.08	-0.84	0.79
	7	59	0.91	4.83	0.88	3.68	1.77	1.31	-0.18	0.90	13.53	9.61	-1.45	2.78	3.09	24.05	1.00
	7	48	0.90	4.69	-0.20	-0.42	0.20	0.71	0.09	-0.37	102.47	285.17	64.33	-73.80	0.91	225.62	1.00
	7	108	0.90	4.67	0.18	0.37	0.56	0.99	-0.05	-1.00	0.88	1.11	-0.11	-0.78	1.55	1.10	0.64
	7	79	0.90	4.60	0.58	1.43	2.25	2.31	-0.76	1.25	35.83	27.91	-13.71	7.62	4.56	34.64	1.00
	7	7	0.90	4.59	0.85	3.17	1.51	0.38	0.42	-1.42	5.15	0.96	1.67	-2.03	1.89	3.45	0.99
	7	109	0.90	4.56	0.66	1.75	0.62	-0.68	0.70	1.44	0.91	-0.52	1.31	0.68	-0.06	-0.05	0.92
	7	76	0.90	4.54	0.66	1.76	0.71	3.16	-0.98	-1.60	1.07	2.06	-1.27	-1.10	3.87	2.30	0.94
	7	260	0.89	4.48	0.98	9.92	1.92	-0.16	-0.02	0.42	2.63	-0.31	-0.05	0.39	1.77	2.70	0.97
	7	330	0.89	4.48	0.84	3.12	-0.25	1.86	0.99	-1.48	-0.16	1.60	0.94	-0.80	1.61	1.45	0.92
	7	123	0.89	4.46	0.46	1.04	0.94	1.07	-0.18	-1.32	15.21	13.64	-4.06	-10.29	2.01	15.88	1.00
	7	22	0.89	4.45	0.84	3.09	0.72	1.53	0.46	1.41	6.32	24.02	5.39	10.38	2.25	20.45	1.00
	7	242	0.89	4.45	0.21	0.42	0.45	0.63	0.82	-1.10	0.56	0.71	0.44	-0.28	1.08	0.73	0.46
	7	13	0.89	4.43	0.60	1.50	0.25	5.91	-2.76	-2.58	0.21	0.98	-0.82	-0.84	6.17	1.04	0.81
	7	32	0.89	4.41	0.94	5.69	1.90	0.50	0.31	0.22	4.09	1.22	0.98	0.24	2.40	3.79	0.99
	7	130	0.89	4.34	0.94	5.72	1.20	-0.23	0.25	-0.86	2.24	-0.34	0.58	-0.74	0.97	1.38	0.95
	7	24	0.89	4.34	0.57	1.38	1.48	2.06	-0.58	-0.57	7.04	7.13	-3.42	-1.13	3.55	8.33	0.99
	7	245	0.89	4.30	0.68	1.88	0.59	0.07	0.68	-1.60	0.97	0.11	0.86	-1.01	0.65	0.59	0.75

Exhibit 2
Apple

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
							Regression Coefficients				Regression T-Stats				Net Effect		
	Years of Data	Total Emp-Years	Level Correlation Coeff	Level Correlation T-Stat	Change Correlation Coeff	Change Correlation T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
[redacted]	7	37	0.88	4.25	-0.04	-0.07	0.57	0.88	-0.53	0.36	1.77	2.44	-2.49	0.57	1.45	2.29	0.89
	7	34	0.88	4.25	0.15	0.30	1.13	2.90	-1.26	0.78	2.87	5.65	-3.68	0.93	4.03	5.04	0.98
	7	8	0.88	4.20	0.89	3.94	1.47	-0.70	0.91	-1.65	9.23	-2.78	5.87	-4.83	0.78	2.62	1.00
	7	103	0.88	4.17	0.40	0.87	0.34	0.62	0.43	-0.72	1.28	1.65	1.75	-1.23	0.96	1.71	0.99
	7	7	0.88	4.15	0.72	2.05	0.53	0.22	-0.32	-0.27	3.42	1.74	-1.18	-0.56	0.75	3.01	0.94
	7	8	0.88	4.11	-0.04	-0.09	0.44	1.15	0.14	-0.78	0.71	1.55	0.31	-0.53	1.58	1.29	0.81
	7	28	0.88	4.08	0.45	1.02	0.07	3.01	-0.73	-2.35	0.56	12.67	-6.31	-6.82	3.09	11.64	1.00
	7	61	0.88	4.08	0.26	0.55	1.31	2.69	-1.24	-1.51	3.08	3.00	-2.32	-2.70	4.00	3.06	0.99
	7	25	0.87	4.01	0.59	1.45	0.28	3.71	-1.43	-0.39	8.63	82.49	-54.77	-6.26	3.99	78.44	1.00
	7	7	0.87	3.98	0.26	0.53	1.98	2.62	-1.42	5.06	1.68	2.14	-1.30	1.91	4.61	2.14	0.98
	7	501	0.87	3.94	0.85	3.21	3.43	-3.62	-0.07	5.76	2.07	-1.57	-0.14	1.48	-0.19	-0.18	0.94
	7	74	0.87	3.94	0.61	1.53	0.61	1.04	0.29	-1.97	1.40	2.07	0.84	-1.88	1.64	2.22	0.93
	7	192	0.87	3.93	-0.50	-1.16	-0.27	0.05	0.31	-0.87	-0.23	0.04	0.66	-0.51	-0.22	-0.10	0.51
	7	11	0.87	3.91	0.49	1.14	-0.28	2.39	-0.62	-0.66	-0.16	0.99	-0.48	-0.16	2.11	0.87	0.81
	7	116	0.87	3.89	0.21	0.43	6.50	7.89	-2.48	6.52	2.32	2.22	-1.95	1.50	14.39	2.27	0.94
	7	239	0.87	3.89	0.89	3.90	0.95	-0.13	0.56	-0.89	1.43	-0.16	1.08	-0.59	0.82	0.81	0.90
	7	10	0.86	3.83	0.54	1.30	-4.35	6.24	-1.52	-7.36	-0.67	0.87	-0.63	-0.57	1.89	0.66	0.80
	7	44	0.86	3.78	0.52	1.22	-0.32	-0.27	0.00	0.96	-0.20	-0.17	0.00	0.74	-0.59	-0.21	0.54
	7	21	0.86	3.69	0.69	1.91	0.77	-0.40	0.84	1.36	0.94	-0.44	1.35	0.74	0.37	0.30	0.95
	7	17	0.85	3.65	0.68	1.84	1.99	1.43	-0.04	-0.81	2.93	1.69	-0.07	-0.45	3.42	2.63	0.97
	7	563	0.85	3.60	0.92	4.56	1.94	-0.26	-0.17	0.60	0.89	-0.17	-0.12	0.17	1.68	1.12	0.84
	7	12	0.85	3.58	0.06	0.12	0.12	0.13	-0.26	-0.46	0.51	0.68	-1.37	-0.74	0.25	0.65	0.79
	7	57	0.85	3.58	0.46	1.03	-0.26	1.45	0.06	1.52	-0.14	1.18	0.06	0.40	1.19	0.60	0.89
	7	145	0.85	3.57	0.90	4.16	1.96	-0.40	-0.23	2.66	15.41	-5.76	-2.47	9.44	1.55	13.27	1.00
	7	33	0.85	3.55	0.04	0.07	0.55	0.93	0.28	-2.78	0.76	0.91	0.66	-3.50	1.48	0.86	0.95
	7	131	0.85	3.55	0.76	2.36	0.54	0.17	0.73	-1.81	1.90	0.72	2.37	-2.35	0.71	1.63	0.96
	7	267	0.84	3.52	-0.16	-0.32	0.22	0.30	1.27	-2.14	0.14	0.19	0.35	-0.20	0.51	0.17	0.51
	7	47	0.84	3.43	0.29	0.60	0.83	1.09	0.45	1.22	1.10	1.76	0.48	0.69	1.91	1.62	0.85
	7	60	0.84	3.42	0.52	1.21	0.83	0.25	-0.30	-0.36	0.54	0.17	-0.26	-0.29	1.09	0.41	0.36
	7	8	0.84	3.40	-0.06	-0.12	0.13	3.20	-1.30	-2.42	0.36	3.70	-2.62	-2.29	3.33	3.00	0.97
	7	50	0.83	3.35	0.61	1.56	0.65	0.05	0.93	-1.56	4.31	0.32	7.83	-4.65	0.70	2.62	1.00
	7	57	0.83	3.34	0.11	0.22	0.25	0.75	0.33	-0.60	0.87	2.96	1.13	-0.67	1.00	2.18	0.95
	7	20	0.83	3.33	0.35	0.75	0.24	0.46	0.59	1.46	0.59	1.17	1.77	1.65	0.70	1.04	0.99
	7	20	0.83	3.32	-0.38	-0.83	-0.34	1.47	-0.20	-0.34	-2.79	7.80	-1.91	-1.02	1.14	3.94	1.00
	7	40	0.82	3.24	0.94	5.74	1.96	-0.82	0.43	0.51	3.60	-1.74	1.46	0.51	1.14	2.01	0.98
	7	144	0.82	3.24	0.91	4.27	1.43	-0.33	0.57	-0.59	1.18	-0.30	0.81	-0.26	1.11	0.79	0.89
	7	23	0.82	3.21	0.55	1.31	-1.37	-5.78	2.74	-18.75	-0.55	-1.16	1.17	-1.69	-7.16	-0.96	0.99
	7	72	0.82	3.17	-0.01	-0.02	-0.59	-0.65	-1.04	2.39	-0.45	-0.50	-0.46	0.44	-1.24	-0.49	0.22
	7	47	0.81	3.07	0.71	2.01	1.22	0.50	0.87	-1.01	2.88	1.31	2.57	-1.08	1.72	2.53	0.98
	7	19	0.80	3.03	0.04	0.08	2.69	4.63	-3.04	0.25	9.26	12.60	-10.11	0.44	7.32	11.71	1.00
	7	49	0.80	3.01	0.92	4.70	1.73	0.34	0.58	-0.22	2.31	0.68	1.06	-0.16	2.08	2.10	0.97
	7	29	0.80	3.01	0.94	5.36	2.26	0.64	-0.32	-0.27	10.93	8.05	-1.48	-1.13	2.90	13.34	1.00
	7	23	0.80	3.01	-0.58	-1.42	-0.22	0.76	0.03	0.23	-0.21	0.66	0.05	0.10	0.54	0.26	0.76
	7	332	0.78	2.78	0.90	4.05	1.12	0.36	0.31	-0.44	4.74	2.55	0.95	-0.89	1.48	4.45	0.99
	7	109	0.77	2.74	0.59	1.45	0.35	-0.21	0.95	-2.33	0.61	-0.28	2.19	-1.70	0.13	0.12	0.92
	7	18	0.77	2.68	0.66	1.76	-0.37	1.16	0.51	1.22	-0.10	0.75	0.29	0.23	0.79	0.20	0.84
	7	15	0.76	2.65	0.89	3.97	1.36	0.10	0.69	-1.38	1.23	0.13	0.90	-0.68	1.47	1.02	0.92
	7	11	0.74	2.49	-0.72	-2.05	-0.09	1.42	-0.90	1.22	-0.09	1.62	-1.38	0.68	1.33	0.76	0.87
	7	103	0.74	2.48	0.30	0.62	0.49	0.98	0.23	-1.43	1.27	2.94	0.68	-1.50	1.47	2.39	0.95
	7	38	0.74	2.45	0.27	0.57	1.08	3.23	-1.67	0.78	1.70	5.32	-3.32	0.56	4.31	4.19	0.98
	7	96	0.73	2.40	0.54	1.29	1.10	0.25	1.33	-1.24	2.47	0.67	3.13	-1.27	1.35	1.85	0.96
	7	103	0.73	2.39	-0.04	-0.08	0.34	0.64	0.29	-2.45	2.71	5.28	3.23	-9.15	0.99	4.33	0.99
	7	135	0.72	2.34	0.07	0.14	-0.09	0.65	0.91	-0.28	-0.15	1.69	1.26	-0.14	0.56	0.68	0.95
	7	14	0.72	2.32	0.74	2.23	-2.58	0.95	3.21	19.13	-0.23	0.38	0.42	1.02	-1.62	-0.12	0.91

Exhibit 2
Apple

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years	Total	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		
	of Data	Emp-Years	Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
[redacted]	7	26	0.70	2.22	0.23	0.48	-0.23	-0.43	0.86	-0.85	-15.24	-28.90	49.37	-12.29	-0.66	-25.59	1.00
	7	25	0.70	2.20	0.68	1.86	0.94	0.69	0.33	-3.50	0.89	0.45	0.39	-1.53	1.62	0.82	0.88
	7	38	0.70	2.20	0.79	2.56	9.17	2.35	-7.19	-19.15	1.03	2.58	-0.73	-0.53	11.52	1.20	0.97
	7	18	0.66	1.95	0.11	0.22	2.32	2.16	-0.46	7.71	1.39	1.67	-0.35	1.99	4.48	1.69	0.93
	7	58	0.66	1.95	0.07	0.15	-0.76	0.61	1.32	-2.62	-1.44	1.90	2.40	-1.36	-0.14	-0.20	0.97
	7	26	0.65	1.90	0.43	0.95	1.80	1.36	-0.95	0.78	1.91	1.85	-0.84	0.32	3.16	2.12	0.83
	7	13	0.65	1.90	0.51	1.18	-1.56	2.39	-0.40	6.21	-0.64	1.99	-0.29	1.79	0.83	0.26	0.97
	7	51	0.64	1.88	0.23	0.47	1.80	1.79	-0.28	0.82	1.11	1.29	-0.21	0.21	3.59	1.32	0.74
	7	14	0.64	1.87	0.38	0.82	0.56	0.52	0.89	-4.00	1.07	1.02	2.18	-3.39	1.08	1.20	0.97
	7	57	0.64	1.86	-0.03	-0.05	-0.09	0.08	1.16	-3.51	-2.94	2.71	47.78	-40.82	-0.01	-0.26	1.00
	7	11	0.63	1.82	0.45	1.01	1.68	1.26	-0.17	-1.18	3.40	3.03	-0.42	-1.01	2.93	3.65	0.97
	7	24	0.63	1.80	0.57	1.40	-0.12	-7.51	4.87	-14.39	-0.13	-2.03	2.22	-3.54	-7.63	-1.69	0.99
	7	127	0.62	1.79	0.04	0.08	2.05	1.96	4.08	-9.17	7.13	7.37	9.16	-8.99	4.01	7.51	0.99
	7	45	0.62	1.79	0.82	2.90	1.18	0.46	0.62	0.77	1.08	0.92	0.50	0.58	1.64	1.07	0.97
	7	36	0.58	1.58	0.86	3.38	3.09	0.55	-1.14	3.47	0.92	0.56	-0.39	0.63	3.64	0.88	0.87
	7	52	0.57	1.57	0.56	1.34	0.91	-0.24	2.01	5.19	0.41	-0.17	1.13	1.29	0.67	0.21	0.91
	7	137	0.56	1.51	0.25	0.51	0.93	0.88	-0.89	-1.03	2.28	2.86	-1.87	-1.16	1.81	2.82	0.94
	7	18	0.55	1.49	0.33	0.69	-0.11	-0.48	2.73	-0.70	-0.25	-1.33	3.40	-0.55	-0.59	-0.78	0.98
	7	13	0.55	1.48	0.52	1.23	0.42	-1.07	2.09	-2.76	0.47	-1.46	3.04	-1.39	-0.65	-0.46	0.97
	7	59	0.55	1.46	0.06	0.12	0.37	0.17	0.75	-5.12	0.25	0.10	0.87	-2.95	0.54	0.18	0.93
	7	16	0.54	1.45	0.47	1.07	3.59	2.10	0.38	3.17	2.25	1.44	0.44	0.55	5.69	1.95	0.93
	7	34	0.54	1.42	0.41	0.90	0.50	-0.48	1.73	-2.69	1.25	-1.52	5.22	-2.97	0.01	0.02	0.98
	7	35	0.53	1.39	0.50	1.17	0.35	-0.64	1.85	-0.64	0.37	-0.92	2.26	-0.30	-0.30	-0.20	0.94
	7	41	0.53	1.38	0.52	1.21	0.82	0.14	0.66	-1.97	1.45	0.32	0.93	-1.55	0.96	1.08	0.86
	7	46	0.52	1.36	0.33	0.69	1.08	1.05	-0.12	0.61	6.60	8.54	-0.68	1.70	2.13	8.30	1.00
	7	15	0.52	1.35	0.73	2.16	0.40	0.56	0.89	-2.38	0.20	0.51	0.62	-0.68	0.96	0.38	0.84
	7	646	0.52	1.35	0.00	0.00	-0.17	-0.16	-0.08	-0.05	-2.19	-2.67	-0.66	-0.17	-0.33	-2.68	0.95
	7	14	0.51	1.33	-0.20	-0.41	0.55	0.31	1.05	0.73	0.34	0.25	0.34	0.15	0.86	0.37	0.55
	7	47	0.51	1.31	0.96	6.64	1.90	-0.37	0.00	0.63	3.25	-1.24	0.00	0.50	1.53	2.14	0.97
	7	27	0.50	1.30	-0.11	-0.23	-1.00	1.69	0.29	-2.35	-5.14	10.67	1.89	-4.56	0.69	2.25	1.00
	7	17	0.49	1.25	0.19	0.38	0.61	0.30	1.50	-1.86	1.24	0.79	3.44	-1.64	0.91	1.17	0.98
	7	13	0.49	1.24	-0.72	-2.07	-2.54	2.26	-1.08	0.56	-0.86	0.91	-0.51	0.10	-0.28	-0.06	0.95
	7	63	0.47	1.20	-0.14	-0.29	-0.42	0.43	1.07	-1.20	-0.49	0.68	1.03	-0.38	0.01	0.01	0.91
	7	85	0.47	1.18	0.43	0.96	0.01	-0.28	1.09	0.67	0.01	-0.41	0.72	0.15	-0.27	-0.14	0.90
	7	60	0.45	1.11	-0.74	-2.18	-0.54	-0.10	0.20	0.50	-1.72	-0.44	0.46	0.35	-0.64	-1.31	0.88
	7	19	0.44	1.10	-0.46	-1.03	0.96	1.03	1.13	-5.03	2.16	3.27	4.56	-5.89	1.98	2.79	1.00
	7	10	0.44	1.08	-0.78	-2.50	-5.10	0.41	-0.38	7.95	-0.71	0.11	-0.12	0.81	-4.69	-0.46	0.79
	7	69	0.42	1.04	-0.10	-0.20	-0.58	-2.48	1.20	12.14	-0.30	-0.89	1.11	0.64	-3.06	-1.33	0.87
	7	36	0.42	1.03	-0.34	-0.73	-0.26	0.23	-0.76	0.15	-1.39	1.93	-2.82	0.32	-0.03	-0.10	0.94
	7	18	0.41	1.01	-0.78	-2.47	-0.78	0.43	0.76	-2.52	-0.18	0.16	0.64	-0.31	-0.36	-0.05	0.81
	7	918	0.41	1.00	0.53	1.24	0.12	-0.15	-0.03	-1.01	3.62	-5.88	-0.58	-9.93	-0.03	-0.56	1.00
	7	127	0.39	0.96	0.22	0.46	1.37	-0.53	2.19	-1.56	1.97	-1.00	3.99	-1.05	0.84	0.77	0.98
	7	25	0.38	0.93	-0.74	-2.21	-0.57	0.13	0.23	0.63	-0.87	0.31	0.29	0.30	-0.43	-0.46	0.85
	7	16	0.38	0.93	0.36	0.78	0.25	-0.84	2.33	-2.61	0.53	-2.31	5.52	-2.38	-0.59	-0.80	0.99
	7	13	0.38	0.91	0.88	3.65	0.55	-0.32	0.73	-1.04	1.59	-1.27	1.52	-1.00	0.23	0.42	0.93
	7	181	0.37	0.90	0.11	0.22	1.10	0.88	1.18	-2.46	0.60	0.62	0.54	-0.65	1.98	0.67	0.52
	7	66	0.37	0.88	0.37	0.81	-2.58	-4.59	3.42	0.76	-1.62	-1.77	1.94	0.77	-7.17	-1.79	0.85
	7	71	0.36	0.86	-0.17	-0.34	-2.34	-1.29	1.86	2.49	-0.88	-0.51	1.11	0.14	-3.63	-1.08	0.86
	7	7	0.34	0.80	0.37	0.79	-0.05	-1.04	1.86	-5.93	-0.34	-8.33	18.36	-20.13	-1.09	-4.77	1.00
	7	33	0.32	0.76	-0.86	-3.42	-2.38	0.60	-0.17	0.62	-0.64	0.27	-0.09	0.11	-1.78	-0.32	0.79
	7	55	0.31	0.73	0.08	0.16	0.42	-0.13	1.60	-2.53	0.67	-0.27	2.48	-1.65	0.29	0.29	0.94
	7	133	0.29	0.68	-0.14	-0.28	-3.16	0.80	2.56	-15.71	-10.86	4.11	10.87	-9.37	-2.36	-6.72	1.00
	7	10	0.26	0.61	0.40	0.87	-1.11	-1.81	3.41	4.00	-0.22	-0.52	0.90	0.41	-2.92	-0.38	0.89
	7	116	0.09	0.20	0.41	0.89	0.90	0.57	-0.01	-0.97	1.77	1.37	-0.02	-0.80	1.46	1.77	0.89

Exhibit 2
Apple

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
							Regression Coefficients				Regression T-Stats				Net Effect		
	Years of Data	Total Emp-Years	Level Correlation Coeff	Level Correlation T-Stat	Change Correlation Coeff	Change Correlation T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
[redacted]	7	29	0.08	0.18	0.33	0.70	0.04	0.09	1.00	-2.10	0.04	0.12	0.78	-0.64	0.13	0.08	0.73
	7	117	0.04	0.08	0.26	0.55	-0.56	1.36	-6.15	1.05	-1.15	3.45	-3.63	0.97	0.80	1.44	0.96
	7	26	-0.04	-0.08	0.21	0.43	-0.76	0.43	1.14	-2.09	-0.93	0.73	1.69	-1.20	-0.34	-0.26	0.99
	7	22	-0.04	-0.10	0.17	0.34	4.02	1.91	-5.35	23.44	2.41	1.95	-2.23	2.84	5.94	2.26	0.97
	7	31	-0.07	-0.16	0.29	0.62	-0.47	-1.28	2.00	-1.97	-0.26	-0.93	1.01	-0.32	-1.74	-0.61	0.64
	7	11	-0.27	-0.63	0.23	0.48	0.75	0.14	0.01	-0.87	0.25	0.05	0.00	-0.37	0.89	0.17	0.21
	7	46	-0.28	-0.66	0.02	0.03	2.17	-1.69	6.68	-6.27	1.26	-1.10	1.77	-1.60	0.48	0.21	0.82
	7	52	-0.36	-0.87	0.37	0.79	1.19	0.84	-0.81	-2.05	2.75	2.07	-1.17	-2.10	2.04	2.78	0.95
	7	50	-0.43	-1.06	-0.96	-6.86	-0.30	0.06	-0.07	-0.09	-6.12	1.64	-0.89	-0.54	-0.24	-3.24	0.99
	7	49	-0.48	-1.23	0.27	0.57	-0.03	-0.11	-0.46	1.13	-0.06	-0.26	-0.43	0.48	-0.14	-0.18	0.55
	7	166	-0.49	-1.25	-0.44	-0.97	-0.12	0.34	-0.76	0.70	-1.22	3.94	-3.94	2.00	0.22	1.43	0.96
	7	36	-0.50	-1.29	0.05	0.10	1.28	3.22	-5.96	8.31	0.99	1.06	-0.97	1.00	4.50	1.10	0.61
	7	21	-0.54	-1.42	0.80	2.66	1.42	0.36	-0.68	-1.28	6.57	1.85	-1.97	-2.37	1.77	4.71	0.99
	7	59	-0.62	-1.79	0.31	0.65	0.43	0.52	-0.51	0.18	0.46	0.58	-0.70	0.24	0.94	0.59	0.48
	7	40	-0.65	-1.92	0.35	0.74	0.75	0.85	-0.63	-0.30	0.43	0.46	-0.41	-0.22	1.61	0.50	0.32
	6	16	0.98	9.32	0.93	4.31											
	6	19	0.96	7.34	0.85	2.85											
	6	54	0.96	7.16	0.89	3.46											
	6	48	0.93	4.91	0.94	4.62											
	6	44	0.87	3.58	0.64	1.18											
	6	20	0.87	3.48	0.45	0.72											
	6	73	0.85	3.24	-0.41	-0.78											
	6	19	0.77	2.41	0.51	1.03											
	6	6	0.76	2.35	-0.46	-0.91											
	6	15	0.76	2.31	0.90	3.49											
	6	24	0.75	2.27	0.08	0.12											
	6	6	0.75	2.26	0.53	1.07											
	6	57	0.73	2.13	-0.47	-0.92											
	6	8	0.72	2.05	0.36	0.55											
	6	10	0.71	2.04	0.55	1.14											
	6	6	0.67	1.81	0.59	1.26											
	6	6	0.63	1.61	0.81	1.95											
	6	8	0.63	1.61	0.82	2.00											
	6	11	0.60	1.49	0.83	2.59											
	6	19	0.59	1.45	0.05	0.08											
	6	12	0.48	1.08	-0.06	-0.09											
	6	19	0.47	1.07	0.04	0.07											
	6	18	0.42	0.93	-0.61	-1.09											
	6	166	0.42	0.92	-0.55	-1.14											
	6	16	0.41	0.89	0.60	1.07											
	6	57	0.38	0.82	-0.32	-0.58											
	6	13	0.36	0.78	-0.14	-0.24											
	6	39	0.34	0.73	0.87	3.11											
	6	18	0.27	0.55	-0.84	-2.21											
	6	8	0.27	0.55	0.78	1.77											
	6	10	0.13	0.27	0.10	0.14											
	6	28	0.13	0.27	0.83	2.58											
	6	12	0.11	0.22	-0.61	-1.10											
	6	24	0.08	0.17	0.12	0.22											
	6	114	0.08	0.16	0.94	4.93											
	6	22	0.04	0.08	0.58	1.22											
	6	6	0.04	0.07	0.90	3.64											
	6	90	-0.01	-0.02	0.26	0.47											
	6	87	-0.11	-0.23	-0.44	-0.84											

Exhibit 2
Apple

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation Coeff	Level Correlation T-Stat	Change Correlation Coeff	Change Correlation T-Stat	Regression Coefficients Contemp	Regression Coefficients Lagged	Regression Coefficients Revenue	Regression Coefficients SJ Emp	Regression T-Stats Contemp	Regression T-Stats Lagged	Regression T-Stats Revenue	Regression T-Stats SJ Emp	Net Effect C + L	Net Effect T-Stat	r2
[redacted]	6	17	-0.16	-0.32	-0.07	-0.13											
	6	16	-0.29	-0.60	0.78	2.16											
	6	6	-0.30	-0.62	-0.55	-1.13											
	6	40	-0.31	-0.65	-0.11	-0.19											
	6	6	-0.45	-1.02	0.84	2.67											
	6	1398	-0.65	-1.70	0.32	0.59											
	6	15	-0.76	-2.36	-0.93	-4.48											
	6	19	-0.85	-3.22	-0.43	-0.83											

Exhibit 2
Google

Job Title	Section 1		Section 2				Section 3					Section 4					Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation		Change Correlation		Regression Coefficients					Regression T-Stats					Net Effect		
			Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp		Contemp	Lagged	Revenue	SJ Emp		C + L	T-Stat	r2
[redacted]			0.94	8.15	0.89	5.63	0.08	0.07	1.36	-2.10		0.45	0.26	3.49	-3.85		0.15	0.37	0.96
			0.91	6.58	0.88	5.21	0.26	0.10	0.73	-0.87		1.01	0.27	1.53	-1.28		0.36	0.62	0.91
			0.91	6.51	0.83	4.27	0.80	0.26	0.48	-1.30		0.87	0.13	0.35	-0.64		1.06	0.37	0.88
			0.86	5.00	0.76	3.30	0.16	0.08	0.70	-1.49		0.40	0.14	0.89	-1.13		0.24	0.26	0.75
			0.82	4.29	0.82	4.05	-0.08	-1.78	2.60	0.26		-0.11	-1.70	2.30	0.15		-1.86	-1.10	0.89
			0.79	3.89	0.78	3.55	-0.21	-1.42	2.46	-2.14		-0.56	-2.52	4.01	-2.41		-1.63	-1.80	0.94
			0.79	3.86	0.75	3.22	0.45	0.57	0.45	-2.87		0.99	0.55	0.79	-1.95		1.02	0.69	0.77
			0.79	3.83	0.61	2.21	-0.27	-0.71	2.24	-3.07		-0.83	-1.34	4.09	-3.87		-0.98	-1.19	0.95
			0.79	3.82	0.84	4.31	0.61	0.50	0.12	-1.31		1.49	0.56	0.20	-1.16		1.11	0.87	0.79
			0.78	3.75	0.82	4.01	0.38	0.24	0.53	-2.31		1.00	0.27	0.99	-1.54		0.62	0.50	0.80
			0.74	3.33	0.75	3.24	0.64	0.88	-0.45	-0.85		2.62	1.79	-1.17	-0.82		1.52	2.14	0.74
			0.71	3.05	0.72	2.91	-0.30	-2.66	3.51	-1.03		-0.32	-1.73	2.31	-0.42		-2.97	-1.23	0.86
			0.71	3.01	0.83	4.25	0.68	0.53	0.03	-1.25		1.35	0.47	0.04	-0.83		1.21	0.75	0.75
			0.70	2.90	0.70	2.78	-0.29	-1.04	1.65	-1.88		-0.93	-2.14	2.97	-1.92		-1.33	-1.73	0.84
			0.67	2.68	0.50	1.64	-0.72	-1.63	2.36	-3.79		-2.59	-3.56	4.96	-5.62		-2.35	-3.28	0.91
			0.62	2.39	0.47	1.52	0.27	0.41	0.37	-1.40		0.48	0.50	0.37	-0.72		0.68	0.51	0.59
			0.59	2.20	0.55	1.84	-1.63	-4.50	5.16	-4.24		-1.47	-2.51	2.86	-1.61		-6.13	-2.16	0.82
			0.56	2.05	0.53	1.77	-2.49	-7.13	7.79	-5.04		-2.28	-3.94	4.41	-1.94		-9.62	-3.40	0.91
			0.51	1.78	0.23	0.66	-1.01	-1.63	2.56	-2.55		-1.52	-1.63	2.14	-1.56		-2.64	-1.62	0.68
			0.48	1.63	0.39	1.21	-0.98	-2.45	3.07	-5.23		-0.85	-1.26	1.94	-2.93		-3.43	-1.12	0.83
			0.27	0.84	-0.02	-0.05	0.15	0.67	0.31	-4.53		0.32	0.91	0.40	-3.20		0.82	0.70	0.75
			0.81	3.90	0.77	3.21	0.35	0.43	0.23	-2.19		1.13	0.64	0.53	-1.75		0.78	0.81	0.77
			0.80	3.75	0.72	2.51	-0.11	-0.45	1.71	-3.16		-0.14	-0.24	1.71	-2.76		-0.56	-0.21	0.90
			0.75	3.16	0.85	4.29	1.58	2.53	-1.92	-2.75		3.14	2.44	-2.19	-1.43		4.11	2.77	0.92
			0.71	2.82	0.47	1.42	1.78	3.60	-2.30	0.40		2.18	2.42	-1.61	0.12		5.38	2.41	0.86
			0.66	2.47	0.50	1.53	1.25	1.78	-1.19	1.94		3.31	3.15	-1.67	1.23		3.03	3.39	0.89
			0.52	1.74	0.62	2.09	0.46	0.10	0.22	1.96		0.71	0.09	0.15	1.13		0.56	0.33	0.63
			0.32	0.95	0.68	2.45	1.20	1.43	-0.38	-3.13		1.21	0.71	-0.24	-1.47		2.62	0.89	0.77
			0.84	4.08	0.82	3.45	1.37	2.09	-0.38	-0.78		4.96	3.34	-0.84	-0.51		3.46	4.07	0.97
			0.78	3.27	0.77	2.94	0.96	1.43	-0.46	1.25		5.78	3.93	-1.70	1.37		2.40	4.80	0.96
			0.73	2.80	0.80	3.23	1.06	1.36	-0.75	0.45		2.63	1.44	-1.12	0.23		2.42	1.86	0.82
			0.71	2.63	0.70	2.43	1.73	2.75	-2.01	1.05		7.82	6.48	-5.33	0.90		4.48	7.35	0.97
			0.67	2.38	0.71	2.45	0.80	0.83	-0.13	0.74		2.41	1.03	-0.21	0.54		1.62	1.47	0.93
			0.64	2.18	0.60	1.84	0.28	0.10	0.34	-0.24		0.63	0.10	0.55	-0.18		0.38	0.27	0.80
			0.56	1.79	0.83	3.70	0.12	0.02	1.64	-0.59		0.18	0.03	1.22	-0.27		0.14	0.11	0.92
			0.44	1.28	0.63	2.00	2.00	0.63	0.47	0.85		0.89	0.16	0.13	0.07		2.63	0.45	0.77
			0.34	0.95	0.18	0.46	1.05	1.92	-0.72	-0.01		1.31	1.32	-0.55	0.00		2.97	1.39	0.63
			0.31	0.86	0.54	1.58	-0.17	-0.39	2.01	1.80		-0.23	-0.39	1.39	0.70		-0.56	-0.34	0.85
			0.26	0.72	0.45	1.12	0.44	0.25	-0.04	1.69		0.59	0.24	-0.03	0.85		0.69	0.39	0.60
			0.22	0.59	0.30	0.77	-0.23	-1.16	2.30	-0.22		-0.78	-2.06	4.60	-0.12		-1.39	-1.72	0.97
			0.09	0.23	-0.11	-0.27	0.35	0.55	0.79	2.64		1.22	1.12	0.93	1.48		0.91	1.23	0.74
			0.06	0.17	0.01	0.02	0.56	1.41	-0.72	-1.11		1.04	1.55	-0.68	-0.37		1.96	1.43	0.74
			-0.15	-0.40	-0.25	-0.64	-2.18	-3.28	3.77	-6.73		-1.31	-1.20	1.38	-0.72		-5.46	-1.31	0.58
			-0.24	-0.66	-0.10	-0.24	-1.80	-3.72	4.55	-2.91		-2.13	-2.64	3.35	-0.63		-5.52	-2.58	0.88
			-0.54	-1.69	-0.22	-0.55	-0.63	-1.27	2.21	-1.20		-1.34	-1.50	2.05	-0.46		-1.90	-1.52	0.70
			0.78	3.05	0.71	2.28	1.10	1.74	0.04	3.10		0.75	0.51	0.02	0.24		2.84	0.58	0.85
			0.78	3.04	0.92	5.32	1.88	2.60	-2.06	-4.37		3.56	1.63	-1.79	-1.79		4.48	2.23	0.96
			0.71	2.50	0.70	2.21	0.75	1.66	0.17	-3.81		2.83	2.60	0.37	-3.67		2.41	2.73	0.96
			0.69	2.34	0.76	2.58	0.56	0.45	0.11	1.61		1.59	0.57	0.16	1.11		1.01	0.92	0.87
			0.64	2.06	0.76	2.65	1.02	1.13	-0.62	2.14		3.30	1.62	-1.01	1.81		2.15	2.18	0.96
			0.55	1.60	0.85	3.66	1.26	-0.55	1.38	2.37		0.69	-0.15	0.40	0.32		0.71	0.14	0.87
			0.51	1.45	0.34	0.81	0.53	0.15	1.09	0.81		0.40	0.05	0.45	0.30		0.68	0.17	0.96
			0.39	1.03	0.49	1.26	0.46	0.80	0.61	0.32		0.75	0.80	0.43	0.22		1.26	0.79	0.95
			0.37	0.97	0.63	1.81	0.32	0.51	1.07	-0.52		0.57	0.58	0.97	-0.59		0.83	0.58	1.00
			0.35	0.91	0.29	0.68	-1.44	-4.65	5.64	-3.81		-0.38	-0.58	0.75	-0.48		-6.10	-0.52	0.92
			0.30	0.76	0.38	0.92	-0.60	-2.22	3.62	4.53		-0.29	-0.54	0.77	0.24		-2.82	-0.47	0.68
			0.21	0.52	0.24	0.55	1.32	1.39	-0.83	8.66		0.97	0.50	-0.31	1.46		2.71	0.67	0.78
			0.20	0.50	-0.11	-0.25	0.76	1.14	0.60	3.34		0.68	0.56	0.33	0.78		1.90	0.61	0.91
			0.17	0.42	0.52	1.36	-0.08	-0.37	1.79	-0.64		-0.26	-0.67	2.41	-0.70		-0.45	-0.53	0.97

Exhibit 2
Google

Job Title	Section 1		Section 2				Section 3					Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation Coeff	Level Correlation T-Stat	Change Correlation Coeff	Change Correlation T-Stat	Regression Coefficients Contemp	Regression Coefficients Lagged	Regression Coefficients Revenue	Regression Coefficients SJ Emp	Regression T-Stats Contemp	Regression T-Stats Lagged	Regression T-Stats Revenue	Regression T-Stats SJ Emp	Net Effect C + L	Net Effect T-Stat	r2
[redacted]			0.11	0.26	0.05	0.12	1.78	4.82	-3.95	-8.75	0.53	0.77	-0.59	-0.38	6.61	0.72	0.69
			0.10	0.25	0.40	0.98	-0.64	-1.19	2.95	-1.74	-0.96	-1.03	2.17	-0.98	-1.83	-1.01	0.98
			0.09	0.22	0.47	1.20	-0.22	-0.67	2.13	-1.85	-0.22	-0.39	1.04	-0.85	-0.89	-0.33	0.96
			0.08	0.19	0.61	1.74	-0.11	-0.73	1.64	0.18	-0.35	-1.26	2.37	0.16	-0.84	-0.97	0.92
			0.00	0.00	0.54	1.44	-0.19	-1.04	2.39	4.19	-0.27	-0.75	1.17	1.85	-1.24	-0.59	0.95
			-0.19	-0.47	0.36	0.87	-0.44	-1.21	2.37	-2.43	-0.85	-1.21	2.05	-1.36	-1.66	-1.10	0.94
			0.94	6.31	0.98	10.15	0.92	0.44	0.15	1.14	1.60	0.34	0.13	0.94	1.36	0.76	0.99
			0.88	4.22	0.98	9.66	1.71	1.08	-1.17	1.74	2.76	0.95	-0.95	1.42	2.78	1.63	0.99
			0.81	3.05	0.93	5.04	2.09	1.73	-1.40	4.09	11.51	5.52	-4.20	10.69	3.82	7.88	1.00
			0.80	2.97	0.89	3.87	1.89	2.59	-2.38	-0.19	1.24	0.96	-0.73	-0.07	4.48	1.07	0.91
			0.78	2.79	0.92	4.85	-0.04	-1.56	2.30	0.05	-0.07	-1.45	2.12	0.04	-1.60	-0.99	0.99
			0.77	2.68	0.87	3.50	-0.01	-0.93	1.40	1.72	-0.03	-1.46	2.31	2.49	-0.94	-1.01	0.99
			0.76	2.60	0.79	2.55	-2.08	-3.14	6.08	-2.19	-1.36	-1.38	1.95	-0.97	-5.22	-1.38	0.98
			0.73	2.36	0.77	2.38	-0.48	-1.11	2.62	0.84	-6.23	-8.70	18.00	7.53	-1.59	-7.81	1.00
			0.72	2.31	0.73	2.15	-2.48	-6.19	6.26	-2.27	-3.18	-3.57	4.53	-2.61	-8.67	-3.46	1.00
			0.70	2.22	0.77	2.40	-0.78	-1.84	3.07	-1.89	-9.88	-12.40	19.74	-11.61	-2.62	-11.63	1.00
			0.69	2.14	0.75	2.28	-0.69	-2.40	3.41	-7.95	-0.25	-0.42	0.61	-1.33	-3.09	-0.37	0.93
			0.67	2.00	0.86	3.38	1.48	1.36	-0.94	2.69	0.97	0.51	-0.33	0.73	2.85	0.69	0.94
			0.64	1.87	0.87	3.48	-0.04	-0.79	1.30	0.83	-0.15	-1.63	2.67	1.56	-0.83	-1.15	0.99
			0.63	1.80	0.55	1.14	0.39	-0.10	2.24	12.58							
			0.62	1.76	0.63	1.61	-0.92	-2.25	3.15	-0.31	-4.54	-5.33	8.35	-0.79	-3.17	-5.10	1.00
			0.61	1.74	0.68	1.83	0.01	-0.21	1.26	0.28	0.02	-0.15	0.74	0.18	-0.20	-0.09	0.89
			0.60	1.68	0.64	1.66	-0.89	-1.99	3.14	-0.82	-5.88	-6.81	10.24	-2.59	-2.88	-6.54	1.00
			0.60	1.67	0.75	2.29	0.41	0.22	0.58	1.15	0.85	0.25	0.60	1.23	0.64	0.47	0.99
			0.57	1.56	0.90	4.02	0.15	-0.71	1.44	1.90	0.22	-0.49	1.27	1.40	-0.56	-0.26	0.97
			0.56	1.52	0.76	2.33	0.78	0.82	-0.11	0.71	1.67	0.94	-0.12	0.79	1.60	1.20	0.99
			0.50	1.29	0.39	0.83	4.23	8.54	-8.63	-7.90	1.16	1.18	-1.07	-1.13	12.77	1.17	0.85
			0.49	1.26	0.67	1.78	1.37	-4.14	4.70	24.13	0.11	-0.20	0.22	0.91	-2.77	-0.08	0.84
			0.47	1.20	0.38	0.82	-0.80	-1.63	2.83	-2.19	-3.13	-3.15	6.13	-4.50	-2.43	-3.16	0.99
			0.44	1.11	0.37	0.81	-1.66	-2.94	4.48	-6.60	-0.97	-0.89	1.31	-1.73	-4.59	-0.92	0.93
			0.44	1.09	0.42	0.92	-0.82	-1.60	2.92	-2.97	-0.73	-0.68	1.34	-1.06	-2.42	-0.70	0.88
			0.43	1.06	0.45	0.99	-0.65	-1.18	2.15	-1.97	-0.59	-0.57	0.99	-0.91	-1.83	-0.58	0.98
			0.41	1.02	0.49	0.79	1.37	2.80	-2.02	0.00							
			0.40	0.97	0.54	1.30	-5.72	-13.34	10.00	5.70	-1.24	-1.29	1.52	1.11	-19.06	-1.27	0.94
			0.23	0.53	0.45	1.01	0.28	0.43	0.82	0.22	0.38	0.26	0.38	0.10	0.71	0.30	1.00
			0.22	0.51	0.16	0.22	2.68	4.65	-1.97	0.00							
			0.21	0.49	0.41	0.90	-0.83	-3.92	4.02	7.39	-2.91	-5.34	6.73	2.49	-4.76	-4.89	0.99
			0.18	0.41	0.31	0.66	-0.20	-0.67	2.19	2.29	-0.92	-1.76	4.10	1.40	-0.87	-1.55	0.98
			0.13	0.29	0.00	-0.01	-0.36	-0.84	1.88	-1.39	-1.32	-1.38	3.83	-0.58	-1.20	-1.43	0.99
			-0.30	-0.69	-0.11	-0.22	3.76	6.86	-6.03	2.52	6.36	5.97	-5.30	2.11	10.62	6.14	1.00
			-0.30	-0.69	-0.60	-1.51	-1.75	-2.91	2.70	-1.26	-2.35	-2.34	2.92	-1.03	-4.65	-2.36	0.94
			0.94	5.52	0.96	5.86											
			0.82	2.84	0.88	3.25											
			0.81	2.78	0.92	4.09											
			0.79	2.55	0.82	2.51											
			0.78	2.53	0.98	9.30											
			0.74	2.19	0.84	2.71											
			0.71	2.02	0.79	2.22											
			0.70	1.99	0.75	1.95											
			0.68	1.86	0.97	6.88											
			0.63	1.62	0.84	2.71											
			0.59	1.45	0.55	1.13											
			0.58	1.44	0.63	1.41											
			0.57	1.40	0.51	1.02											
			0.56	1.37	0.63	1.40											
			0.54	1.30	0.56	1.17											
			0.54	1.27	0.75	1.95											
			0.52	1.21	0.78	2.19											
			0.47	1.06	0.48	0.94											

Exhibit 2
Google

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years of Data	Total Emp-Years	Level Correlation Coeff	Level Correlation T-Stat	Change Correlation Coeff	Change Correlation T-Stat	Regression Coefficients Contemp	Regression Coefficients Lagged	Regression Coefficients Revenue	Regression Coefficients SJ Emp	Regression T-Stats Contemp	Regression T-Stats Lagged	Regression T-Stats Revenue	Regression T-Stats SJ Emp	Net Effect C + L	Net Effect T-Stat	r2
[redacted]			0.44	0.99	0.60	1.32											
			0.42	0.93	0.50	0.99											
			0.38	0.83	0.42	0.81											
			0.35	0.74	0.27	0.49											
			0.34	0.72	0.64	1.45											
			0.30	0.63	0.95	3.20											
			0.30	0.63	0.18	0.32											
			0.29	0.61	0.17	0.30											
			0.25	0.51	0.18	0.32											
			0.22	0.45	0.08	0.14											
			0.19	0.39	0.55	1.13											
			0.15	0.31	0.30	0.45											
			0.14	0.29	0.37	0.69											
			0.12	0.23	0.15	0.27											
			0.10	0.20	0.58	1.24											
			0.09	0.18	0.01	0.01											
			0.07	0.13	0.07	0.12											
			-0.04	-0.09	-0.37	-0.69											
			-0.05	-0.11	-0.28	-0.51											
			-0.24	-0.48	-0.60	-1.31											

Exhibit 2
Intel

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years	Total	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		
	of Data	Emp-Years	Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
[redacted]	11	432	0.96	10.82	0.95	8.41	2.03	-0.51	0.64	-0.34	6.11	-0.78	1.25	-0.76	1.52	1.78	0.95
	11	1501	0.96	9.78	0.94	7.56	1.56	0.30	0.32	-0.54	6.76	0.36	0.73	-1.63	1.86	2.07	0.96
	11	233	0.94	8.46	0.91	6.14	1.47	1.33	-0.23	-0.09	4.71	0.74	-0.25	-0.15	2.80	1.46	0.92
	11	3042	0.94	8.03	0.89	5.67	0.61	0.39	-0.20	0.31	7.76	2.09	-1.33	1.93	1.00	4.39	0.95
	11	5042	0.92	7.30	0.91	6.21	0.81	2.22	-0.06	-0.63	3.59	2.93	-0.23	-2.53	3.03	4.40	0.96
	11	293	0.91	6.73	0.89	5.46	2.30	0.95	-0.19	-0.45	4.05	0.63	-0.18	-0.54	3.25	1.88	0.88
	11	724	0.88	5.65	0.94	8.07	1.43	0.58	0.19	-0.55	1.48	0.38	0.39	-1.04	2.00	2.26	0.91
	11	59	0.88	5.56	0.72	2.91	1.12	0.73	0.22	-0.33	2.35	0.84	0.37	-0.49	1.85	1.54	0.81
	11	394	0.88	5.52	0.88	5.34	0.63	0.35	-0.13	0.06	4.97	1.77	-0.54	0.30	0.98	3.77	0.87
	11	3991	0.88	5.51	0.96	9.32	1.21	0.07	0.45	-0.45	5.45	0.12	2.00	-1.73	1.28	2.52	0.97
	11	715	0.86	4.96	0.96	9.29	1.41	-0.28	0.49	-0.32	4.26	-0.51	1.60	-0.87	1.13	2.18	0.95
	11	437	0.85	4.85	0.84	4.41	0.76	0.75	0.30	-0.49	4.90	1.85	1.46	-2.05	1.51	3.13	0.95
	11	6082	0.85	4.85	0.94	7.51	0.81	0.45	0.34	-0.48	6.95	1.58	2.34	-2.61	1.27	4.17	0.97
	11	912	0.85	4.76	0.94	7.60	0.95	0.69	0.20	-0.59	3.95	1.52	0.76	-1.49	1.64	3.53	0.94
	11	31	0.84	4.74	0.82	4.00	0.59	0.35	0.44	-0.13	3.17	0.95	1.78	-0.52	0.94	2.06	0.91
	11	216	0.83	4.50	0.83	4.23	0.66	0.62	0.09	0.03	4.10	2.02	0.34	0.08	1.28	3.57	0.93
	11	1681	0.83	4.45	0.92	6.69	0.78	0.39	0.30	-0.37	5.05	1.16	1.60	-1.35	1.17	3.20	0.96
	11	103	0.81	4.17	0.87	4.91	0.76	0.70	0.09	-0.30	4.60	2.74	0.41	-1.11	1.46	4.40	0.93
	11	2903	0.81	4.12	0.95	8.50	0.92	0.20	0.32	-0.30	8.74	0.80	2.51	-1.67	1.12	4.24	0.98
	11	413	0.81	4.11	0.95	8.85	0.88	0.38	0.07	-0.09	5.34	1.23	0.34	-0.31	1.26	3.91	0.95
	11	1438	0.81	4.08	0.93	7.04	0.96	0.63	0.02	-0.19	3.97	1.40	0.08	-0.43	1.58	3.38	0.92
	11	2235	0.80	4.01	0.89	5.55	0.73	0.22	0.42	-0.36	7.48	1.12	3.34	-2.29	0.95	4.04	0.98
	11	4821	0.80	4.00	0.96	9.45	0.80	0.19	0.27	-0.26	12.44	1.28	3.21	-2.23	1.00	5.90	0.99
	11	638	0.80	3.98	0.91	6.09	0.77	0.53	0.13	-0.22	4.39	1.74	0.59	-0.74	1.31	3.66	0.94
	11	760	0.80	3.97	0.93	7.45	0.94	0.34	0.23	-0.29	5.66	1.03	1.16	-1.11	1.28	3.47	0.96
	11	501	0.79	3.91	0.88	5.24	0.75	0.24	0.46	-0.50	4.67	0.68	2.22	-1.90	0.99	2.42	0.96
	11	1538	0.79	3.90	0.91	6.15	0.78	0.20	0.22	-0.05	3.77	0.59	0.79	-0.17	0.98	2.32	0.90
	11	292	0.79	3.89	0.82	4.10	0.70	0.83	0.05	-0.23	3.30	2.23	0.16	-0.52	1.53	3.43	0.85
	11	528	0.79	3.81	0.75	3.23	0.84	1.07	0.36	-0.95	4.51	2.41	1.37	-3.86	1.91	3.58	0.96
	11	75	0.78	3.80	0.81	3.88	2.04	0.36	0.21	-0.24	3.00	0.25	0.19	-0.23	2.40	1.22	0.83
	11	244	0.78	3.78	0.90	5.76	0.68	0.61	0.06	-0.23	9.04	4.38	0.55	-1.62	1.29	7.24	0.97
	11	5735	0.78	3.75	0.91	6.32	0.76	0.29	0.30	-0.31	6.40	1.23	2.00	-1.53	1.06	3.83	0.97
	11	2120	0.78	3.72	0.95	9.08	0.74	0.29	0.11	-0.08	11.59	2.62	1.25	-0.67	1.03	7.72	0.99
	11	328	0.77	3.66	0.77	3.41	0.75	0.71	0.38	-0.88	4.32	2.20	1.67	-3.46	1.46	3.53	0.93
	11	1011	0.77	3.64	0.91	6.37	0.74	0.36	-0.06	0.16	6.31	1.72	-0.35	0.66	1.09	4.25	0.95
	11	811	0.77	3.62	0.84	4.31	0.67	0.44	0.10	-0.20	3.33	1.31	0.35	-0.63	1.11	2.49	0.81
	11	262	0.77	3.61	0.91	6.02	0.75	0.54	0.02	-0.17	4.38	2.21	0.07	-0.64	1.28	4.18	0.92
	11	1332	0.77	3.61	0.92	6.65	0.79	0.51	0.18	-0.35	4.64	1.60	0.85	-1.17	1.30	3.57	0.94
	11	104	0.77	3.57	0.84	4.35	0.53	0.19	0.54	-0.50	4.55	0.98	3.37	-2.61	0.72	2.80	0.96
	11	91	0.76	3.52	0.89	5.55	1.09	0.23	-0.37	0.29	3.84	0.37	-0.82	0.50	1.32	2.15	0.83
	11	127	0.75	3.44	0.90	6.00	0.35	0.00	0.00	0.08	3.84	0.02	0.00	0.63	0.35	1.75	0.86
	11	1525	0.75	3.43	0.89	5.39	0.78	0.45	-0.05	0.15	5.52	1.98	-0.25	0.54	1.24	4.20	0.95
	11	9515	0.75	3.39	0.86	4.86	0.89	0.85	-0.21	0.02	4.12	2.74	-0.75	0.06	1.74	4.39	0.91
	11	369	0.74	3.35	0.97	10.62	0.80	0.28	0.13	-0.19	12.18	2.90	1.51	-1.69	1.08	8.85	0.99
	11	6476	0.74	3.31	0.97	10.58	0.88	0.17	0.11	-0.05	9.63	1.06	0.97	-0.28	1.05	5.69	0.98
	11	73	0.74	3.27	0.54	1.83	0.69	1.21	-0.10	-0.26	3.46	4.54	-0.32	-0.91	1.91	5.11	0.90
	11	1580	0.74	3.26	0.93	7.07	0.83	0.46	0.21	-0.44	4.96	1.46	1.03	-1.57	1.30	3.58	0.95
	11	165	0.73	3.24	0.94	7.74	0.74	0.42	0.07	-0.14	12.31	4.81	0.79	-1.28	1.16	10.29	0.99
	11	573	0.73	3.18	0.97	11.28	0.74	0.18	-0.01	0.08	10.93	1.79	-0.09	0.67	0.92	7.00	0.98
	11	155	0.72	3.15	0.91	6.37	1.26	-0.07	0.62	-0.88	3.47	-0.14	1.57	-2.13	1.20	1.99	0.92
	11	598	0.72	3.14	0.89	5.39	0.65	0.32	0.32	-0.39	5.41	1.65	2.06	-1.93	0.97	3.95	0.97
	11	548	0.72	3.11	0.82	4.03	0.60	0.45	0.46	-0.71	2.24	0.98	1.36	-1.45	1.05	1.88	0.88
	11	1676	0.72	3.08	0.94	7.83	0.64	0.29	-0.03	0.09	12.56	3.94	-0.39	1.04	0.93	9.19	0.99
	11	473	0.72	3.07	0.93	7.05	0.78	0.23	0.24	-0.21	11.30	1.86	2.72	-1.66	1.00	6.68	0.99
	11	402	0.71	3.06	0.88	5.17	0.60	0.22	0.25	-0.11	4.23	1.02	1.29	-0.47	0.82	2.88	0.94
	11	373	0.71	3.04	0.89	5.66	0.86	0.10	0.41	-0.58	3.13	0.26	1.26	-1.61	0.96	1.92	0.89

Exhibit 2
Intel

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years	Total	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		
	of Data	Emp-Years	Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
[redacted]	11	1906	0.71	3.04	0.97	10.58	0.85	0.22	0.13	-0.14	9.03	1.52	1.05	-0.83	1.07	6.07	0.98
	11	3531	0.71	3.03	0.89	5.61	0.72	0.21	0.33	-0.26	7.95	1.32	2.79	-1.66	0.93	4.71	0.98
	11	934	0.71	3.03	0.92	6.73	0.72	0.36	0.04	-0.02	7.71	2.74	0.33	-0.10	1.08	6.22	0.98
	11	1873	0.71	3.02	0.96	9.25	0.85	0.36	0.21	-0.43	9.91	2.60	2.01	-2.80	1.21	7.24	0.99
	11	130	0.71	2.99	0.90	5.77	0.86	0.03	0.42	-0.38	3.38	0.07	1.28	-0.96	0.89	1.59	0.89
	11	2037	0.70	2.98	0.92	6.42	0.63	0.23	0.18	-0.11	8.43	1.93	1.78	-0.85	0.86	5.50	0.98
	11	88	0.70	2.98	0.91	6.08	0.69	0.06	0.27	-0.13	3.97	0.21	1.20	-0.54	0.75	2.06	0.91
	11	366	0.70	2.95	0.95	8.65	0.67	0.18	0.16	-0.11	13.19	2.16	2.20	-1.16	0.85	8.03	0.99
	11	137	0.70	2.94	0.67	2.53	0.71	0.37	0.76	-0.67	3.37	1.01	2.72	-2.35	1.08	2.16	0.96
	11	828	0.70	2.92	0.93	7.12	0.63	0.27	-0.10	0.06	5.89	1.78	-0.60	0.37	0.89	4.25	0.92
	11	969	0.70	2.91	0.91	6.08	0.66	0.35	-0.18	0.26	6.39	2.57	-1.14	1.47	1.01	5.16	0.94
	11	87	0.69	2.89	0.75	3.25	0.92	1.57	-0.16	-0.84	4.41	3.84	-0.58	-2.69	2.49	5.00	0.93
	11	179	0.69	2.87	0.87	5.06	0.64	0.05	0.57	-0.77	5.02	0.28	3.39	-4.03	0.69	2.74	0.96
	11	8983	0.69	2.87	0.96	9.77	0.78	0.25	-0.03	0.09	12.24	2.56	-0.35	0.73	1.03	8.27	0.99
	11	934	0.69	2.86	0.96	10.05	0.83	0.15	0.12	-0.04	12.79	1.57	1.42	-0.31	0.98	8.03	0.99
	11	1049	0.69	2.85	0.89	5.67	0.68	0.28	0.40	-0.60	4.91	1.15	2.29	-2.62	0.96	3.24	0.96
	11	146	0.69	2.84	0.65	2.41	0.39	0.43	0.29	-0.16	1.82	1.34	1.00	-0.52	0.82	1.81	0.84
	11	509	0.69	2.84	0.89	5.51	0.70	0.18	0.30	-0.17	4.88	0.78	1.58	-0.74	0.88	2.97	0.95
	11	1402	0.69	2.83	0.94	7.53	0.77	0.19	0.26	-0.34	4.41	0.81	1.16	-1.27	0.96	3.11	0.94
	11	2097	0.68	2.81	0.97	11.50	0.78	0.15	0.07	-0.02	13.52	1.65	0.91	-0.15	0.93	8.04	0.99
	11	268	0.68	2.77	0.95	8.82	0.83	0.00	0.24	-0.10	7.42	-0.01	1.66	-0.55	0.83	3.85	0.97
	11	546	0.68	2.76	0.94	7.55	0.72	0.29	0.07	-0.04	10.66	2.99	0.76	-0.29	1.01	7.77	0.99
	11	12004	0.68	2.75	0.95	8.95	0.76	0.28	-0.02	0.07	16.18	4.10	-0.24	0.81	1.04	11.58	0.99
	11	577	0.67	2.74	0.96	9.51	0.82	0.18	0.02	0.02	6.42	1.06	0.12	0.08	1.00	4.25	0.95
	11	50	0.67	2.72	0.45	1.42	1.17	0.66	0.28	-0.65	1.34	0.35	0.19	-0.47	1.83	0.73	0.66
	11	358	0.67	2.72	0.85	4.50	0.58	0.40	-0.23	0.30	4.89	2.47	-1.27	1.51	0.98	4.17	0.90
	11	753	0.67	2.70	0.97	11.28	0.91	0.20	-0.12	0.25	18.00	2.81	-1.70	2.54	1.11	11.93	0.99
	11	517	0.67	2.69	0.84	4.39	0.49	0.28	0.06	0.02	3.39	1.48	0.26	0.07	0.77	2.76	0.87
	11	547	0.67	2.68	0.95	9.06	0.78	0.29	0.08	-0.16	9.05	2.41	0.68	-1.08	1.07	6.51	0.98
	11	834	0.66	2.67	0.94	7.57	0.81	0.02	0.36	-0.27	8.80	0.16	3.17	-1.75	0.83	4.89	0.99
	11	556	0.66	2.66	0.89	5.49	0.73	0.28	-0.05	0.02	3.34	1.08	-0.15	0.07	1.00	2.64	0.84
	11	361	0.66	2.65	0.55	1.88	1.08	1.40	-0.82	0.92	4.01	3.26	-2.79	2.83	2.48	3.84	0.79
	11	955	0.66	2.65	0.95	8.72	0.67	0.22	-0.09	0.12	6.90	1.62	-0.63	0.72	0.89	4.72	0.95
	11	188	0.66	2.64	0.88	5.23	0.67	0.43	-0.06	0.11	7.43	3.15	-0.46	0.60	1.09	5.97	0.97
	11	169	0.66	2.63	0.92	6.63	0.78	-0.01	0.43	-0.34	4.71	-0.04	2.09	-1.30	0.77	2.49	0.96
	11	91	0.66	2.62	0.84	4.34	1.85	0.51	0.49	-0.64	3.26	0.37	0.49	-0.66	2.36	1.55	0.91
	11	94	0.66	2.60	0.84	4.32	0.61	0.00	0.79	-0.89	1.50	0.00	1.68	-1.45	0.61	0.89	0.87
	11	59	0.65	2.59	0.81	3.93	0.97	0.78	-0.29	0.10	2.52	1.75	-0.57	0.15	1.75	2.67	0.82
	11	537	0.65	2.59	0.97	11.61	0.81	0.20	0.12	-0.17	12.42	2.35	1.33	-1.54	1.01	8.64	0.99
	11	249	0.65	2.59	0.78	3.47	0.69	0.54	-0.26	0.23	3.24	1.77	-0.82	0.62	1.23	2.81	0.77
	11	557	0.65	2.58	0.90	5.76	0.61	0.06	0.35	-0.26	4.22	0.27	1.84	-1.16	0.67	2.34	0.94
	11	1504	0.65	2.54	0.90	5.82	0.64	0.19	0.22	-0.12	4.79	1.02	1.19	-0.54	0.82	3.28	0.95
	11	159	0.64	2.53	0.85	4.66	0.60	0.38	0.23	-0.42	3.11	1.51	0.77	-1.05	0.97	2.75	0.87
	11	629	0.64	2.51	0.94	7.72	0.84	0.25	-0.04	0.15	6.63	1.51	-0.25	0.67	1.09	4.72	0.96
	11	427	0.64	2.50	0.87	5.03	0.58	0.23	0.07	0.02	3.76	1.03	0.32	0.07	0.81	2.57	0.88
	11	498	0.64	2.49	0.91	6.15	0.51	0.13	0.12	-0.02	4.81	0.92	0.74	-0.12	0.64	3.09	0.93
	11	465	0.64	2.49	0.92	6.44	0.72	0.14	0.13	-0.04	4.33	0.57	0.55	-0.16	0.86	2.54	0.91
	11	7219	0.64	2.47	0.93	7.41	0.70	0.15	-0.07	0.21	6.35	0.90	-0.43	1.00	0.85	3.70	0.94
	11	641	0.64	2.47	0.97	10.80	0.70	0.06	0.07	0.06	21.06	1.36	1.47	1.02	0.76	11.66	1.00
	11	1364	0.63	2.45	0.95	8.60	0.84	0.26	-0.09	0.15	7.62	1.56	-0.57	0.63	1.10	5.05	0.96
	11	117	0.63	2.44	0.86	4.68	0.66	0.34	0.73	-1.36	1.62	0.75	1.47	-1.93	1.00	1.57	0.87
	11	3942	0.63	2.42	0.97	10.47	0.80	0.17	0.06	-0.07	7.41	1.11	0.37	-0.39	0.97	4.63	0.96
	11	198	0.63	2.42	0.75	3.16	0.68	0.59	0.33	-0.81	1.45	0.87	0.59	-1.25	1.26	1.42	0.78
	11	9310	0.63	2.40	0.93	7.13	0.67	0.26	-0.11	0.23	12.47	3.48	-1.33	2.29	0.93	8.81	0.99
	11	910	0.62	2.40	0.94	7.87	0.72	0.22	0.02	0.05	6.85	1.61	0.13	0.28	0.94	4.81	0.96
	11	1690	0.62	2.39	0.96	10.06	0.63	0.21	-0.01	-0.03	9.53	2.25	-0.08	-0.26	0.84	6.39	0.97

Exhibit 2
Intel

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years	Total	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		
	of Data	Emp-Years	Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
[redacted]	11	283	0.62	2.37	0.94	7.52	0.65	0.05	0.30	-0.25	7.48	0.42	2.54	-1.81	0.71	4.13	0.98
	11	142	0.62	2.37	0.83	4.28	0.72	0.31	0.18	-0.06	8.01	2.32	1.48	-0.33	1.03	5.73	0.99
	11	2959	0.62	2.36	0.92	6.75	0.72	0.20	0.13	-0.05	8.49	1.69	1.18	-0.35	0.92	5.64	0.98
	11	880	0.62	2.36	0.93	7.34	0.70	0.32	-0.11	0.18	16.35	5.74	-1.75	2.20	1.03	12.77	0.99
	11	202	0.61	2.34	0.85	4.49	0.77	0.28	0.22	-0.61	5.44	1.53	1.16	-2.85	1.05	3.95	0.94
	11	1662	0.61	2.32	0.91	6.38	0.61	0.23	0.05	0.04	6.83	1.91	0.38	0.23	0.85	4.89	0.97
	11	731	0.61	2.29	0.94	7.46	0.95	0.31	-0.11	0.18	5.47	1.49	-0.46	0.60	1.26	4.15	0.94
	11	2205	0.61	2.29	0.68	2.62	0.68	0.79	-0.41	0.54	4.01	2.68	-2.34	2.66	1.47	3.36	0.81
	11	2086	0.61	2.29	0.95	8.39	0.76	0.23	0.10	-0.10	11.64	2.61	1.13	-0.81	0.99	8.19	0.99
	11	1156	0.61	2.29	0.71	2.86	0.74	0.86	-0.51	0.62	6.12	4.08	-4.06	4.03	1.60	5.14	0.91
	11	91	0.61	2.29	0.64	2.33	0.90	1.18	0.26	-1.23	2.02	1.38	0.41	-2.07	2.07	1.92	0.87
	11	1393	0.60	2.26	0.84	4.44	0.72	0.19	0.02	0.05	2.62	0.50	0.06	0.13	0.90	1.70	0.74
	11	96	0.60	2.26	0.84	4.38	0.60	0.15	0.30	-0.21	2.16	0.44	0.84	-0.51	0.75	1.50	0.84
	11	281	0.60	2.25	0.80	3.74	0.73	0.65	-0.11	-0.15	3.57	2.18	-0.38	-0.43	1.37	3.32	0.84
	11	128	0.60	2.24	0.94	7.89	0.75	0.26	-0.11	0.04	6.10	1.57	-0.60	0.20	1.01	4.27	0.93
	11	601	0.60	2.23	0.91	6.20	0.57	0.17	0.08	0.06	7.66	1.70	0.72	0.46	0.74	5.09	0.97
	11	303	0.60	2.23	0.55	1.87	0.48	0.48	0.59	-0.82	1.84	1.14	1.74	-2.12	0.96	1.62	0.90
	11	147	0.59	2.21	0.85	4.64	0.47	0.12	0.26	-0.16	5.01	0.93	2.02	-1.06	0.59	3.12	0.96
	11	261	0.59	2.20	0.68	2.60	0.63	0.93	0.49	-1.91	1.52	1.85	1.07	-3.78	1.56	2.22	0.93
	11	282	0.59	2.19	0.68	2.59	0.54	0.63	-0.41	0.42	4.24	3.97	-1.95	1.85	1.18	4.79	0.89
	11	223	0.59	2.18	0.88	5.13	0.59	0.14	0.15	-0.09	2.98	0.53	0.52	-0.31	0.72	1.93	0.83
	11	5107	0.59	2.18	0.95	8.21	0.84	0.24	0.15	-0.28	5.52	1.16	0.75	-1.03	1.08	3.87	0.95
	11	213	0.59	2.18	0.82	4.07	0.45	0.03	0.45	-0.36	2.95	0.14	2.19	-1.50	0.48	1.57	0.92
	11	347	0.58	2.15	0.93	6.90	0.76	0.02	0.21	-0.24	3.83	0.08	0.78	-0.66	0.79	1.98	0.88
	11	135	0.58	2.15	0.76	3.34	0.38	0.13	0.15	0.03	2.29	0.56	0.61	0.13	0.50	1.49	0.80
	11	1471	0.58	2.13	0.93	7.06	0.65	0.32	-0.21	0.23	8.65	3.35	-1.84	1.76	0.97	6.81	0.96
	11	2090	0.58	2.13	0.95	9.03	0.60	0.18	0.03	-0.01	8.79	1.97	0.27	-0.07	0.79	5.91	0.97
	11	197	0.58	2.13	0.91	6.18	0.77	0.16	0.05	-0.05	3.57	0.62	0.15	-0.13	0.94	2.36	0.86
	11	35	0.58	2.12	0.76	3.32	0.76	0.57	0.11	-0.36	1.09	0.86	0.14	-0.34	1.33	1.21	0.72
	11	159	0.57	2.11	0.85	4.48	0.98	0.74	-0.47	0.30	4.51	2.97	-1.57	0.79	1.72	4.57	0.90
	11	126	0.57	2.10	0.69	2.71	1.14	1.07	-0.90	0.54	4.38	3.53	-2.14	1.07	2.21	4.76	0.86
	11	223	0.57	2.09	0.95	8.28	0.68	0.18	0.13	-0.18	6.80	1.40	0.96	-1.01	0.86	4.66	0.97
	11	934	0.57	2.08	0.91	6.20	0.82	0.33	-0.01	0.06	6.86	2.24	-0.05	0.28	1.15	5.30	0.97
	11	403	0.57	2.07	0.87	4.91	0.55	0.13	0.29	-0.30	3.25	0.58	1.23	-1.05	0.68	2.07	0.89
	11	1801	0.57	2.06	0.96	9.45	0.70	0.22	0.06	-0.09	13.13	3.09	0.78	-0.93	0.91	9.09	0.99
	11	400	0.57	2.06	0.85	4.49	0.67	0.45	-0.41	0.40	5.67	2.89	-2.06	1.68	1.11	4.91	0.90
	11	390	0.57	2.06	0.88	5.26	0.57	0.16	0.17	-0.11	3.80	0.78	0.81	-0.43	0.73	2.48	0.91
	11	115	0.56	2.04	0.57	1.97	0.29	0.20	0.31	-0.21	1.24	0.60	0.89	-0.54	0.49	1.00	0.64
	11	556	0.56	2.03	0.95	8.49	0.65	0.18	0.00	0.02	6.90	1.45	0.01	0.13	0.84	4.56	0.95
	11	120	0.56	2.03	0.62	2.25	0.48	0.36	0.00	-0.07	1.78	0.90	0.00	-0.15	0.83	1.46	0.50
	11	5274	0.56	2.02	0.92	6.52	0.60	0.23	-0.29	0.32	6.74	1.85	-2.08	2.13	0.83	4.58	0.93
	11	1349	0.56	2.01	0.85	4.53	0.74	0.46	-0.15	-0.10	4.78	2.27	-0.65	-0.40	1.20	4.06	0.88
	11	29	0.56	2.01	0.59	2.04	0.58	0.34	0.51	-0.46	0.98	0.40	0.67	-0.59	0.93	0.76	0.66
	11	83	0.56	2.00	0.61	2.18	1.56	1.26	-1.03	0.95	2.13	0.97	-0.99	0.70	2.82	1.62	0.49
	11	120	0.54	1.91	0.70	2.80	0.45	0.23	0.24	-0.29	1.75	0.70	0.55	-0.58	0.68	1.36	0.66
	11	167	0.54	1.91	0.47	1.53	0.64	1.07	0.19	-0.58	1.25	1.71	0.23	-0.65	1.71	1.82	0.62
	11	379	0.53	1.90	0.85	4.56	0.43	0.14	0.20	-0.18	3.10	0.78	0.93	-0.77	0.57	2.13	0.86
	11	164	0.53	1.89	0.89	5.65	0.64	0.30	-0.11	0.09	4.61	1.67	-0.52	0.35	0.94	3.52	0.89
	11	57	0.53	1.89	0.23	0.68	0.06	0.28	0.22	0.10	0.35	1.17	0.89	0.36	0.33	0.94	0.77
	11	2080	0.53	1.89	0.91	6.07	0.62	0.33	-0.32	0.36	9.83	4.08	-3.13	3.14	0.95	7.84	0.97
	11	92	0.53	1.89	0.86	4.78	1.23	-0.01	0.01	-0.02	2.89	-0.01	0.02	-0.03	1.22	1.18	0.74
	11	225	0.53	1.86	0.19	0.56	2.13	5.05	-3.95	3.09	1.46	2.76	-2.11	1.66	7.18	2.51	0.81
	11	1020	0.53	1.86	0.96	9.33	0.69	0.06	0.14	-0.06	9.28	0.59	1.33	-0.47	0.75	5.24	0.98
	11	209	0.52	1.85	0.90	5.89	0.93	0.43	-0.28	0.07	5.65	2.15	-1.20	0.29	1.36	4.54	0.91
	11	732	0.52	1.82	0.88	5.35	0.66	0.43	-0.28	0.18	7.75	3.94	-2.08	1.18	1.08	6.67	0.95
	11	567	0.51	1.79	0.84	4.34	0.55	0.25	0.04	-0.15	3.28	1.11	0.17	-0.53	0.81	2.41	0.81

Exhibit 2
Intel

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years	Total	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		
	of Data	Emp-Years	Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
[redacted]	11	147	0.51	1.78	0.54	1.81	1.24	1.41	-0.21	0.81	1.90	1.26	-0.23	0.75	2.66	1.76	0.77
	11	86	0.51	1.77	0.79	3.65	1.01	0.67	-0.58	0.49	3.20	1.85	-1.27	1.00	1.68	2.97	0.78
	11	102	0.50	1.75	0.81	3.91	0.54	0.33	0.22	-0.52	3.49	1.69	0.97	-1.88	0.87	2.97	0.90
	11	4667	0.50	1.75	0.98	12.47	0.61	0.16	-0.13	0.18	23.02	4.67	-3.16	3.88	0.77	14.83	0.99
	11	1283	0.50	1.74	0.96	9.47	0.92	0.32	-0.18	0.20	11.04	3.34	-1.57	1.40	1.24	8.41	0.98
	11	54	0.50	1.74	0.57	1.94	0.57	-0.03	0.42	-0.12	0.99	-0.03	0.60	-0.17	0.54	0.38	0.54
	11	222	0.49	1.67	0.70	2.76	0.62	0.56	-0.36	0.29	2.67	1.82	-0.99	0.69	1.18	2.61	0.70
	11	43	0.48	1.66	0.60	2.11	0.79	1.05	-0.64	0.46	2.16	2.61	-1.17	0.66	1.84	2.77	0.79
	11	56	0.47	1.62	0.76	3.30	0.53	0.16	0.41	-0.70	1.48	0.37	0.91	-1.23	0.70	1.05	0.81
	11	536	0.46	1.56	0.88	5.16	0.70	-0.04	0.16	-0.24	3.19	-0.13	0.51	-0.82	0.66	1.60	0.81
	11	7841	0.46	1.55	0.94	7.67	0.82	0.32	-0.37	0.32	9.49	2.99	-2.82	2.15	1.14	7.10	0.96
	11	325	0.46	1.55	0.68	2.65	0.21	-0.18	0.74	-0.69	1.37	-0.86	3.29	-2.77	0.04	0.12	0.89
	11	249	0.46	1.54	0.53	1.79	1.23	1.07	-0.31	0.93	1.94	0.98	-0.36	0.84	2.29	1.50	0.62
	11	666	0.46	1.54	0.96	9.70	0.68	0.13	-0.01	-0.03	6.56	1.02	-0.06	-0.15	0.81	4.14	0.94
	11	150	0.46	1.54	0.91	6.38	0.52	0.03	0.28	-0.35	6.29	0.24	2.44	-2.80	0.55	3.42	0.96
	11	106	0.44	1.49	0.78	3.50	0.66	0.53	-0.14	-0.07	2.86	2.01	-0.44	-0.16	1.19	2.82	0.87
	11	101	0.44	1.46	0.72	2.94	0.57	0.04	0.50	-0.56	1.39	0.07	0.93	-0.89	0.62	0.76	0.76
	11	1976	0.44	1.46	0.83	4.16	0.68	0.48	-0.47	0.38	6.73	3.82	-2.95	2.20	1.16	5.99	0.92
	11	353	0.43	1.43	0.82	4.00	0.71	0.28	-0.25	0.20	2.97	0.92	-0.68	0.53	0.99	2.16	0.72
	11	56	0.43	1.42	0.49	1.57	1.04	1.39	-0.40	-0.48	1.87	1.86	-0.52	-0.57	2.43	2.24	0.67
	11	137	0.43	1.42	0.87	4.89	0.81	0.36	-0.30	0.35	3.47	1.33	-0.87	0.85	1.18	2.78	0.83
	11	105	0.42	1.38	0.86	4.75	0.84	0.39	-0.31	0.05	6.05	2.44	-1.50	0.24	1.23	4.84	0.92
	11	125	0.41	1.34	0.58	2.03	0.57	0.70	-0.34	0.12	2.36	2.39	-0.99	0.34	1.27	2.77	0.77
	11	117	0.41	1.33	0.58	2.03	0.53	-0.23	0.87	-1.07	0.83	-0.25	1.07	-1.28	0.30	0.24	0.67
	11	65	0.40	1.32	-0.02	-0.07	0.48	1.30	-0.35	0.08	1.01	2.07	-0.47	0.10	1.78	1.85	0.59
	11	156	0.38	1.22	0.74	3.13	0.60	0.32	-0.49	0.61	3.02	1.23	-1.54	1.64	0.92	2.34	0.73
	11	35	0.35	1.14	0.59	2.08	0.13	-0.31	0.80	-0.34	0.31	-0.61	1.51	-0.55	-0.18	-0.23	0.82
	11	98	0.35	1.12	0.57	1.97	0.63	0.55	-0.53	0.51	1.92	1.28	-1.03	0.93	1.18	1.83	0.50
	11	225	0.34	1.10	0.71	2.82	0.58	-0.08	0.58	-0.82	1.30	-0.14	0.92	-1.07	0.50	0.59	0.67
	11	171	0.34	1.08	0.80	3.76	0.70	0.12	-0.43	0.34	3.96	0.49	-1.54	1.13	0.82	2.35	0.78
	11	45	0.34	1.08	0.50	1.62	0.09	-0.43	1.15	-1.06	0.44	-1.56	3.87	-3.50	-0.34	-0.82	0.87
	11	533	0.34	1.07	0.41	1.28	1.15	1.12	-0.12	1.23	1.70	1.00	-0.13	1.01	2.27	1.42	0.66
	11	243	0.33	1.05	0.86	4.84	0.61	0.24	-0.31	0.42	4.09	1.26	-1.28	1.53	0.85	2.92	0.85
	11	774	0.33	1.04	0.83	4.27	0.45	0.16	-0.02	0.16	3.29	0.89	-0.08	0.75	0.60	2.26	0.86
	11	47	0.29	0.92	0.73	3.05	0.47	-0.13	0.47	-0.46	1.38	-0.30	1.06	-0.98	0.34	0.53	0.69
	11	199	0.27	0.84	0.60	2.10	0.44	0.37	-0.19	0.36	1.43	0.96	-0.38	0.55	0.81	1.32	0.68
	11	111	0.25	0.76	0.48	1.56	0.31	0.18	0.21	-0.29	1.00	0.46	0.51	-0.68	0.49	0.81	0.53
	11	30	0.21	0.64	0.09	0.25	0.14	0.54	-0.12	0.12	0.33	0.99	-0.19	0.19	0.68	0.80	0.43
	11	31	0.17	0.52	0.66	2.46	0.23	-0.65	0.88	-0.73	0.98	-1.97	2.75	-2.07	-0.42	-0.85	0.79
	11	361	0.12	0.38	0.79	3.70	0.59	0.11	-0.24	0.14	3.26	0.46	-0.90	0.50	0.70	1.96	0.71
	11	734	-0.03	-0.08	0.47	1.51	0.65	-0.02	0.22	-0.63	3.20	-0.07	0.77	-2.03	0.63	1.49	0.84
	10	901	0.92	6.51	0.96	9.16	1.00	1.35	0.01	-0.46	15.91	4.71	0.11	-2.98	2.35	7.74	0.99
	10	102	0.91	6.40	0.96	8.44	0.74	0.98	0.53	-0.89	3.30	2.03	1.81	-2.45	1.72	3.81	0.98
	10	1266	0.90	5.74	0.83	3.66	1.53	0.26	0.50	-0.39	4.28	0.19	0.67	-0.91	1.78	1.16	0.96
	10	952	0.88	5.29	0.92	6.33	1.18	0.77	-0.03	0.15	5.46	1.56	-0.11	0.39	1.95	3.84	0.96
	10	529	0.84	4.32	0.94	7.21	0.69	0.27	0.27	-0.19	6.57	1.38	1.92	-1.09	0.97	4.10	0.97
	10	186	0.84	4.30	0.98	12.18	0.58	0.14	0.08	-0.07	11.57	1.62	1.10	-0.83	0.72	6.46	0.98
	10	262	0.82	4.10	0.82	3.73	0.59	0.48	-0.14	0.23	3.88	1.95	-0.45	0.61	1.07	3.34	0.86
	10	391	0.81	3.94	0.91	5.67	0.77	0.74	0.20	-0.06	5.36	3.11	1.24	-0.25	1.51	5.96	0.98
	10	1514	0.79	3.64	0.97	9.92	0.76	0.29	0.13	-0.09	8.76	2.15	1.07	-0.58	1.05	6.44	0.98
	10	30	0.78	3.53	0.77	2.94	0.81	-0.01	0.72	-0.73	2.23	-0.01	1.42	-1.61	0.80	0.80	0.90
	10	794	0.76	3.31	0.88	4.88	0.54	0.32	0.04	0.00	3.95	1.57	0.20	0.02	0.86	3.10	0.88
	10	25	0.75	3.21	0.69	2.31	0.85	0.88	0.44	-0.76	1.86	2.05	0.80	-0.99	1.73	2.23	0.93
	10	1764	0.74	3.12	0.96	9.71	0.68	0.20	0.15	-0.09	10.13	1.90	1.56	-0.78	0.88	6.55	0.98
	10	50	0.72	2.97	0.55	1.62	0.85	0.33	0.16	-0.42	1.54	0.42	0.28	-0.75	1.18	0.95	0.73
	10	189	0.71	2.89	0.39	1.04	0.20	0.58	0.07	-0.14	0.57	1.23	0.16	-0.27	0.78	1.17	0.77

Exhibit 2
Intel

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years	Total	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		
	of Data	Emp-Years	Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
[redacted]	10	149	0.69	2.70	0.84	3.75	0.24	1.11	0.15	-0.83	0.32	2.13	0.30	-1.34	1.35	1.70	0.92
	10	1401	0.68	2.61	0.96	9.53	0.72	0.27	0.06	-0.09	9.38	2.52	0.50	-0.62	0.99	6.88	0.98
	10	81	0.68	2.61	0.75	2.96	1.20	1.12	-0.39	0.27	2.19	1.58	-0.57	0.35	2.31	2.29	0.76
	10	1872	0.63	2.29	0.95	8.08	0.69	0.29	-0.05	0.06	8.10	2.53	-0.42	0.42	0.98	6.08	0.97
	10	53	0.62	2.26	0.46	1.25	0.68	0.75	0.23	-0.32	5.31	4.85	1.71	-1.26	1.42	5.73	0.97
	10	31	0.61	2.20	0.94	7.06	1.28	-0.42	0.82	-1.13	5.65	-1.31	2.71	-3.26	0.86	2.03	0.98
	10	40	0.60	2.09	0.89	5.10	1.03	0.47	0.29	-0.81	2.39	0.97	0.62	-1.30	1.50	2.17	0.90
	10	951	0.59	2.06	0.93	6.70	0.62	0.30	-0.24	0.25	10.29	3.72	-2.57	2.31	0.92	7.78	0.97
	10	20	0.58	2.04	0.56	1.66	0.30	-0.27	0.47	-0.38	1.05	-0.68	1.35	-0.78	0.03	0.04	0.87
	10	37	0.58	2.04	0.89	4.84	1.29	0.23	0.09	0.05	2.39	0.41	0.19	0.08	1.51	2.05	0.90
	10	113	0.57	1.98	0.73	2.61	0.21	0.27	0.20	0.09	0.34	0.52	0.37	0.15	0.48	0.52	0.81
	10	464	0.57	1.97	0.82	3.86	0.84	0.93	0.34	-0.18	1.89	1.44	0.72	-0.27	1.77	2.36	0.95
	10	86	0.55	1.88	0.56	1.64	1.30	2.76	0.18	-0.29	2.28	1.89	0.22	-0.34	4.05	2.12	0.73
	10	29	0.48	1.55	0.90	5.35	0.63	0.27	0.06	-0.22	4.22	1.40	0.28	-0.76	0.90	3.16	0.90
	10	107	0.48	1.54	0.78	3.31	0.67	0.81	0.22	-0.33	3.00	3.39	0.89	-0.77	1.48	4.16	0.98
	10	878	0.47	1.52	0.92	6.26	0.96	0.40	-0.12	0.15	4.86	1.53	-0.43	0.32	1.37	3.79	0.93
	10	42	0.46	1.45	0.87	4.28	0.72	0.53	0.35	-0.76	0.50	0.79	0.45	-1.06	1.24	0.73	0.95
	10	281	0.45	1.42	0.66	2.34	0.30	0.20	0.23	-0.09	1.79	0.88	0.85	-0.28	0.50	1.48	0.78
	10	49	0.37	1.13	0.94	7.27	0.64	-0.15	0.13	-0.28	5.60	-0.83	0.83	-1.38	0.49	2.03	0.93
	10	340	0.34	1.02	0.92	6.08	0.52	0.16	0.11	-0.21	6.64	1.52	0.96	-1.61	0.68	4.43	0.96
	10	44	0.26	0.78	0.91	5.82	1.04	-0.03	0.32	-0.06	3.33	-0.08	0.84	-0.10	1.01	1.83	0.91
	10	42	0.26	0.76	0.79	3.13	3.52	1.68	-0.54	1.64	6.75	2.12	-0.79	1.94	5.21	4.68	0.97
	10	157	0.23	0.68	0.40	1.17	0.28	0.30	0.16	-0.07	0.52	0.43	0.22	-0.09	0.58	0.54	0.43
	10	20	-0.28	-0.83	-0.32	-0.88	0.07	0.37	0.13	-1.18	0.16	0.68	0.21	-1.75	0.44	0.52	0.68
	10	40	-0.34	-1.02	-0.48	-1.45	-0.16	0.33	-0.16	-1.00	-0.30	0.52	-0.25	-1.38	0.17	0.16	0.68
	9	72	0.84	4.12	0.73	2.59	2.09	0.76	0.09	-1.59	1.57	0.30	0.04	-0.56	2.86	0.82	0.81
	9	46	0.78	3.34	0.77	2.94	1.06	0.67	0.54	-0.76	1.37	0.24	0.30	-0.43	1.73	0.56	0.81
	9	105	0.78	3.31	0.79	3.13	1.15	0.86	0.01	0.49	16.00	9.29	0.16	3.20	2.02	14.45	0.99
	9	18	0.77	3.16	0.75	2.57	0.57	0.15	0.76	-0.64	0.99	0.19	1.43	-0.64	0.72	0.80	0.89
	9	50	0.75	3.01	0.85	3.89	0.77	0.92	0.37	-1.82	0.50	0.82	0.35	-0.91	1.69	0.90	0.87
	9	64	0.75	2.98	0.92	4.79	3.72	0.33	-1.05	1.80	1.60	0.23	-0.69	0.79	4.05	1.75	0.92
	9	172	0.72	2.73	0.85	3.92	0.82	0.28	0.19	-0.33	1.36	0.33	0.19	-0.26	1.10	0.91	0.75
	9	50	0.61	2.03	0.70	2.19	0.92	0.94	-0.21	0.16	3.01	1.38	-0.49	0.26	1.86	2.00	0.97
	9	67	0.43	1.26	0.21	0.49	0.05	-0.30	0.88	-0.96	0.13	-0.54	1.61	-1.59	-0.26	-0.31	0.71
	9	17	0.36	1.01	0.55	1.31	5.91	3.81	-2.42	0.48	2.49	2.36	-2.09	0.41	9.72	3.51	0.96
	9	13	0.17	0.46	0.58	1.41	0.10	-0.15	0.52	-0.29	0.10	-0.12	0.49	-0.29	-0.05	-0.02	0.79
	9	52	0.08	0.22	0.60	1.81	1.09	0.34	0.38	-0.65	3.50	1.05	1.09	-0.99	1.43	2.58	0.95
	8	283	0.99	17.90	0.97	9.74	0.86	-0.01	0.14	-0.01	6.72	-0.02	1.05	-0.05	0.85	1.38	0.97
	8	864	0.98	12.28	0.98	9.96	0.75	0.36	0.18	-0.24	12.01	1.90	2.63	-1.88	1.12	5.69	0.99
	8	1526	0.98	11.20	0.96	7.28	0.74	-0.02	0.19	-0.29	4.74	-0.04	1.16	-0.93	0.72	1.51	0.95
	8	50	0.97	10.69	0.96	7.81	0.91	0.17	-0.09	-0.12	4.85	0.29	-0.41	-0.31	1.08	1.69	0.94
	8	420	0.97	10.36	0.97	8.73	0.74	0.26	0.09	-0.37	14.77	1.66	1.63	-3.65	1.00	6.01	1.00
	8	288	0.97	9.49	0.94	6.39	0.61	-0.04	0.04	-0.20	3.39	-0.12	0.20	-0.59	0.56	1.27	0.91
	8	1097	0.96	8.48	0.93	5.58	0.33	0.09	0.08	-0.19	6.90	1.22	1.57	-2.02	0.42	4.06	0.98
	8	92	0.96	8.30	0.89	4.29	0.96	0.07	0.18	0.08	2.47	0.07	0.43	0.10	1.04	0.95	0.83
	8	1185	0.96	8.16	0.87	4.03	0.83	1.18	0.23	-0.63	6.14	1.86	1.17	-2.32	2.01	3.07	0.98
	8	119	0.95	7.73	0.95	6.85	2.48	0.75	-0.22	-0.28	10.75	1.97	-0.77	-0.58	3.23	6.38	0.99
	8	51	0.94	7.02	0.78	2.77	1.06	-0.02	0.37	-1.71	1.74	-0.02	0.46	-1.30	1.04	0.65	0.87
	8	355	0.94	6.66	0.83	3.30	0.43	0.46	0.05	-0.18	6.58	3.98	0.68	-1.37	0.89	5.85	0.97
	8	52	0.93	6.35	0.93	4.25	0.95	1.33	-0.16	-0.76					2.27		1.00
	8	34	0.93	6.18	0.79	2.87	1.11	1.33	0.17	-0.44	5.31	2.15	0.87	-1.46	2.44	3.08	0.97
	8	303	0.92	5.96	0.93	5.53	0.90	0.61	0.24	-0.11	2.37	0.56	0.68	-0.16	1.52	1.58	0.93
	8	258	0.92	5.71	0.90	4.56	0.79	0.15	0.00	-0.13	2.48	0.24	0.01	-0.20	0.94	1.20	0.82
	8	143	0.92	5.70	0.92	5.17	1.24	0.94	0.02	0.19	3.82	1.16	0.06	0.30	2.18	2.46	0.93
	8	24	0.91	5.51	0.96	7.81	1.50	-0.86	1.10	-1.27	6.40	-2.06	3.94	-4.57	0.64	1.47	0.99
	8	612	0.91	5.50	0.81	3.09	0.44	-0.08	0.40	-0.43	2.85	-0.31	2.41	-1.42	0.36	1.01	0.93

Exhibit 2
Intel

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years	Total	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		
	of Data	Emp-Years	Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
[redacted]	8	359	0.91	5.42	0.84	3.53	0.59	-0.10	0.50	-0.47	4.46	-0.38	3.44	-1.76	0.49	1.50	0.97
	8	152	0.91	5.32	0.67	2.01	0.43	0.75	0.12	-0.29	3.08	3.03	0.66	-1.03	1.18	3.69	0.92
	8	98	0.90	5.00	0.94	6.09	1.44	0.21	0.34	-0.88	2.61	0.25	0.71	-0.98	1.65	2.00	0.94
	8	374	0.90	4.94	0.70	2.19	0.58	0.04	0.53	-0.61	1.66	0.04	1.49	-1.07	0.62	0.51	0.92
	8	689	0.90	4.92	0.94	6.39	0.87	1.50	0.11	-0.83	1.67	1.34	0.30	-1.87	2.37	3.38	0.99
	8	203	0.88	4.53	0.95	6.80	2.06	0.25	0.42	-0.73	43.99	2.43	7.04	-9.31	2.32	23.84	1.00
	8	291	0.87	4.41	0.94	6.05	0.64	0.46	0.13	-0.17	7.62	3.81	1.42	-1.07	1.10	7.90	0.99
	8	65	0.86	4.07	0.65	1.90	1.50	0.76	-1.51	1.81	3.06	1.28	-1.46	3.42	2.26	5.65	0.95
	8	318	0.84	3.77	0.91	4.83	0.65	0.35	0.12	-0.06	4.53	1.09	0.46	-0.15	1.00	2.51	0.98
	8	24	0.83	3.68	0.74	2.49	0.68	2.29	-0.04	-3.04	1.06	2.31	-0.04	-1.88	2.97	2.25	0.94
	8	217	0.82	3.50	0.96	7.70	0.63	0.17	-0.21	0.27	32.69	6.94	-8.81	6.75	0.80	22.98	1.00
	8	201	0.82	3.49	0.84	3.43	0.54	0.30	-0.04	0.29	3.36	1.40	-0.22	0.89	0.84	2.75	0.88
	8	214	0.81	3.36	0.94	6.24	0.62	0.24	-0.01	-0.06	5.00	1.47	-0.07	-0.25	0.86	3.82	0.96
	8	304	0.81	3.36	0.52	1.37	0.23	-0.07	0.37	-0.43	0.84	-0.18	1.44	-0.91	0.16	0.25	0.72
	8	266	0.80	3.32	0.91	4.94	0.48	-0.43	0.41	-0.06	4.05	-1.36	2.10	-0.27	0.05	0.12	0.98
	8	116	0.80	3.30	0.91	4.95	0.62	0.34	0.34	-0.76	6.72	2.40	3.96	-4.87	0.95	6.30	0.99
	8	180	0.78	3.03	0.88	4.13	0.40	0.16	0.13	0.04	2.75	0.51	0.48	0.12	0.56	1.37	0.94
	8	1077	0.77	2.97	0.92	5.43	0.57	0.26	0.09	-0.20	5.81	2.02	0.83	-1.08	0.83	4.79	0.98
	8	155	0.77	2.92	0.95	6.98	0.93	0.43	0.15	0.20	9.92	4.50	1.94	1.44	1.36	12.17	1.00
	8	57	0.76	2.91	0.54	1.45	1.12	1.05	-0.14	1.02	2.78	1.86	-0.43	1.65	2.17	2.40	0.80
	8	48	0.76	2.90	0.40	0.99	0.70	0.73	0.12	0.95	4.75	3.51	0.65	3.27	1.44	4.66	0.95
	8	64	0.76	2.90	0.56	1.52	0.81	1.22	-0.14	0.05	1.51	1.36	-0.12	0.04	2.02	1.58	0.70
	8	246	0.76	2.87	0.93	5.66	0.99	-0.13	-0.37	0.25	6.76	-0.56	-2.17	0.84	0.86	3.16	0.97
	8	157	0.75	2.81	0.88	4.13	0.60	0.45	0.59	-0.51	1.01	0.65	1.45	-0.67	1.06	1.60	0.94
	8	33	0.75	2.81	0.83	3.26	2.33	0.41	-1.63	0.25	2.80	0.74	-2.32	0.76	2.74	6.78	0.98
	8	41	0.75	2.81	0.39	0.95	0.84	0.76	0.40	0.84	2.52	1.52	1.13	1.30	1.60	2.23	0.90
	8	87	0.75	2.79	0.11	0.24	0.77	1.02	0.04	0.44	1.60	1.67	0.10	0.68	1.79	1.75	0.62
	8	62	0.75	2.77	0.94	6.08	0.71	0.47	0.37	-0.27	85.90	58.69	59.28	-22.97	1.17	129.23	1.00
	8	72	0.75	2.75	0.37	0.89	0.42	0.15	0.43	-0.35	0.63	0.13	0.81	-0.32	0.57	0.33	0.67
	8	69	0.72	2.56	0.20	0.46	0.04	0.06	0.24	-0.32	0.34	0.35	1.65	-1.25	0.10	0.41	0.76
	8	10	0.72	2.51	0.15	0.34	0.79	1.77	-0.84	0.75	0.58	1.22	-0.48	0.26	2.56	1.06	0.64
	8	460	0.71	2.50	0.91	5.04	0.53	0.31	0.03	-0.20	8.28	3.96	0.37	-1.66	0.84	7.81	0.99
	8	29	0.71	2.44	0.29	0.67	0.18	0.87	0.37	-1.00	0.59	1.92	1.14	-1.66	1.05	1.65	0.93
	8	53	0.70	2.38	0.41	1.00	0.47	0.78	0.27	0.65	0.89	1.19	0.45	0.62	1.25	1.31	0.74
	8	102	0.69	2.34	0.66	1.76	1.06	2.22	-0.21	-0.04	3.56	2.14	-0.18	-0.03	3.28	2.68	0.95
	8	33	0.69	2.32	0.74	2.47	1.60	0.84	-1.27	1.94	8.75	5.92	-5.09	5.55	2.44	10.41	0.99
	8	324	0.67	2.23	0.58	1.60	0.29	0.18	0.23	0.05	2.30	1.15	1.57	0.20	0.47	2.02	0.90
	8	14	0.67	2.20	0.55	1.48	1.25	0.61	0.13	1.89	6.47	2.56	0.58	4.51	1.86	5.42	0.98
	8	132	0.65	2.11	0.94	5.98	0.89	0.41	-0.13	-0.37	5.32	2.31	-0.80	-1.43	1.30	5.86	0.98
	8	34	0.65	2.10	0.52	1.38	0.59	0.38	0.09	0.89	10.55	5.92	1.33	7.48	0.96	10.05	0.99
	8	79	0.65	2.08	0.85	3.63	0.62	-0.05	0.59	-1.07	1.95	-0.11	1.98	-1.94	0.57	1.11	0.95
	8	730	0.56	1.65	0.64	1.86	0.68	0.64	-0.30	0.87	5.55	5.21	-1.91	3.72	1.32	6.73	0.97
	8	1281	0.55	1.60	0.61	1.71	0.53	0.64	-0.17	0.62	3.75	4.51	-0.97	2.35	1.17	5.18	0.96
	8	355	0.52	1.51	0.79	2.88	0.72	0.44	-0.25	0.06	1.72	1.02	-0.51	0.08	1.16	1.83	0.76
	8	206	0.48	1.33	0.76	2.59	0.64	0.48	-0.37	0.49	3.56	2.52	-1.65	1.38	1.13	3.80	0.90
	8	4110	0.47	1.30	0.91	4.91	1.00	0.51	-0.33	0.45	5.46	3.02	-1.71	1.44	1.52	5.74	0.97
	8	644	0.46	1.26	0.88	4.20	0.56	0.31	-0.10	0.24	6.06	3.00	-0.96	1.35	0.87	5.57	0.97
	8	108	0.45	1.24	-0.42	-1.03	0.73	0.61	0.36	0.72	0.39	0.34	0.25	0.27	1.34	0.39	0.74
	8	64	0.45	1.24	0.74	2.44	0.77	0.88	-0.32	0.58	2.46	3.63	-0.96	1.22	1.65	3.75	0.95
	8	23	0.44	1.19	0.47	1.18	0.54	0.53	0.02	0.79	1.33	1.22	0.03	0.97	1.07	1.56	0.75
	8	82	0.43	1.18	0.31	0.72	0.42	0.30	0.30	0.17	0.65	0.36	0.44	0.13	0.72	0.57	0.47
	8	412	0.39	1.04	-0.03	-0.07	0.18	0.64	-0.14	0.58	1.06	3.52	-0.61	1.70	0.82	2.81	0.91
	8	434	0.37	0.98	0.91	5.06	0.62	0.30	-0.01	-0.13	4.92	2.26	-0.08	-0.59	0.91	4.64	0.97
	8	97	0.26	0.65	0.13	0.30	0.31	0.33	0.16	0.99	2.27	2.30	0.93	3.30	0.65	2.74	0.97
	8	41	0.19	0.48	0.43	1.06	1.06	-0.70	1.54	-0.95	0.70	-0.30	0.82	-0.31	0.36	0.11	0.76
	8	151	0.10	0.24	-0.46	-1.15	-0.41	-0.50	0.48	-0.43	-2.83	-3.01	3.66	-1.77	-0.91	-3.25	0.90

Exhibit 2
Intel

Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years	Total	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		
	of Data	Emp-Years	Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
[redacted]	8	17	0.09	0.23	0.04	0.10	-0.56	-0.38	1.10	-1.61	-0.55	-0.23	0.59	-0.80	-0.94	-0.37	0.70
	7	104	0.99	14.44	0.82	2.85	1.14	1.18	-0.09	-0.01	1.48	1.03	-0.25	-0.01	2.32	1.59	0.85
	7	163	0.99	13.23	0.85	3.20	0.57	0.15	0.26	-0.17	170.84	47.89	194.68	-80.66	0.71	117.74	1.00
	7	283	0.98	10.30	0.90	4.19	0.89	0.35	0.06	-0.14	2.34	1.14	0.36	-0.51	1.24	1.91	0.97
	7	245	0.97	9.67	0.79	2.57	1.32	0.61	-0.15	0.49	3.19	2.10	-0.84	1.67	1.94	2.94	0.95
	7	236	0.97	8.77	0.68	1.87	1.14	0.88	-0.17	0.10	17.95	15.99	-6.89	2.33	2.02	18.15	1.00
	7	18	0.96	8.21	0.38	0.82	-0.14	0.87	-0.01	-0.31	-0.12	1.14	-0.02	-0.36	0.73	0.49	0.87
	7	43	0.95	7.10	0.23	0.47	0.31	0.93	0.23	-0.25	0.21	0.95	0.33	-0.22	1.24	0.59	0.60
	7	26	0.95	6.90	0.26	0.53	-0.70	0.15	0.73	-1.01	-0.49	0.12	1.14	-1.09	-0.55	-0.21	0.84
	7	116	0.95	6.82	0.67	1.83	0.38	0.04	0.24	-0.10	2.45	0.44	4.00	-1.02	0.42	1.74	0.99
	7	38	0.95	6.61	0.71	2.03	0.38	0.23	0.56	-0.87	0.16	0.16	0.55	-0.48	0.61	0.19	0.77
	7	118	0.94	6.35	0.25	0.52	0.97	1.19	0.03	-0.07	3.96	6.27	0.33	-0.46	2.16	5.16	0.99
	7	331	0.94	6.31	0.74	2.23	0.48	1.24	0.22	0.07	0.32	0.76	0.30	0.05	1.72	0.69	0.87
	7	23	0.94	6.28	0.30	0.64	1.69	1.01	-0.35	1.06	8.89	8.16	-3.65	7.14	2.70	9.52	0.99
	7	47	0.94	6.16	-0.04	-0.08	0.69	0.12	-0.28	1.02	4.52	0.77	-3.15	7.38	0.81	3.08	0.99
	7	58	0.94	6.02	0.84	3.08	0.65	0.16	0.42	-0.70	0.37	0.12	0.54	-0.54	0.81	0.32	0.84
	7	389	0.93	5.80	0.58	1.41	0.81	0.37	-0.06	0.32	1.48	1.15	-0.25	0.87	1.19	1.41	0.83
	7	114	0.92	5.11	0.86	3.44	0.98	1.26	-0.50	0.28	9.71	4.95	-2.37	1.04	2.24	7.23	0.99
	7	78	0.91	4.78	0.84	3.06	0.64	0.46	0.57	-0.63	3.30	1.03	1.65	-1.35	1.10	1.96	0.98
	7	11	0.91	4.77	0.56	1.36	0.52	0.56	0.59	-0.99	0.18	0.33	0.46	-0.38	1.09	0.28	0.74
	7	10	0.90	4.64	-0.21	-0.43	-0.52	0.03	0.29	0.55	-0.13	0.02	0.15	0.17	-0.48	-0.09	0.38
	7	154	0.90	4.59	0.89	3.86	0.70	-0.35	0.38	-0.27	0.72	-0.53	0.94	-0.44	0.34	0.22	0.92
	7	38	0.89	4.28	0.91	4.34	2.43	1.12	-0.12	0.31	1.55	1.02	-0.19	0.28	3.56	1.80	0.95
	7	57	0.88	4.22	-0.01	-0.03	0.30	1.33	0.01	0.44	0.14	0.80	0.01	0.23	1.63	0.45	0.68
	7	14	0.88	4.19	0.79	2.58	1.41	1.63	-0.08	0.17	3.38	1.26	-0.13	0.20	3.04	1.94	0.96
	7	93	0.88	4.10	0.51	1.17	0.39	0.53	0.14	-0.10	0.19	0.43	0.15	-0.07	0.91	0.31	0.54
	7	12	0.87	3.95	-0.28	-0.59	1.73	1.98	0.00	0.02	155.52	275.61	-0.38	3.81	3.72	205.65	1.00
	7	61	0.86	3.80	0.51	1.18	-2.12	-1.62	1.89	-2.71	-2.11	-1.70	3.49	-4.25	-3.75	-1.93	0.99
	7	40	0.86	3.79	0.46	1.03	0.91	0.00	-0.55	0.22	0.56	0.00	-0.99	0.23	0.91	0.33	0.75
	7	70	0.86	3.74	0.39	0.84	-0.20	-0.03	0.30	-1.19	-0.15	-0.03	0.65	-1.40	-0.23	-0.11	0.92
	7	81	0.86	3.72	0.78	2.53	1.55	-1.09	1.49	-0.68	2.23	-2.74	5.13	-1.23	0.46	0.53	1.00
	7	45	0.86	3.70	0.69	1.91	1.92	1.03	-0.04	0.46	1.64	1.63	-0.07	0.53	2.95	1.79	0.93
	7	35	0.85	3.68	0.64	1.66	-0.36	-0.35	0.80	-1.47	-0.46	-0.60	2.23	-2.45	-0.71	-0.54	0.97
	7	8	0.85	3.62	0.43	0.95	-3.96	-4.09	3.34	-7.26	-2.93	-3.93	4.56	-5.07	-8.05	-3.88	0.98
	7	90	0.85	3.55	0.67	1.79	1.34	0.61	-0.07	0.26	6.07	4.89	-0.77	1.70	1.94	5.87	0.99
	7	82	0.84	3.43	0.15	0.31	2.16	1.13	-0.81	1.24	2.08	1.99	-1.91	1.82	3.29	2.12	0.83
	7	31	0.84	3.42	0.72	2.06	1.23	1.76	-0.59	0.20	0.98	0.50	-0.27	0.13	2.99	0.65	0.75
	7	569	0.83	3.32	0.32	0.67	0.93	0.64	-0.26	0.11	1.39	1.68	-0.95	0.23	1.57	1.55	0.89
	7	15	0.82	3.24	0.74	2.23	2.26	1.27	-0.47	0.09	0.83	0.48	-0.55	0.07	3.53	0.67	0.78
	7	17	0.82	3.23	-0.32	-0.69	0.87	2.52	-0.26	1.72	0.39	1.54	-0.33	0.81	3.38	0.89	0.95
	7	39	0.82	3.22	0.14	0.27	-5.32	-2.53	3.26	-4.08	-1.61	-1.16	1.98	-1.77	-7.85	-1.51	0.91
	7	83	0.80	3.02	0.86	3.43	2.81	0.85	-0.20	0.69	2.06	1.02	-0.32	0.68	3.67	1.84	0.94
	7	123	0.80	2.98	0.53	1.26	0.33	0.33	0.45	-0.39	0.17	0.30	0.53	-0.27	0.66	0.23	0.78
	7	32	0.78	2.78	0.28	0.58	1.45	2.36	-0.44	-0.57	0.39	0.82	-0.23	-0.22	3.81	0.58	0.96
	7	351	0.77	2.72	0.64	1.69	-0.31	-0.68	1.13	-1.28	-0.19	-0.62	1.51	-1.12	-0.99	-0.39	0.93
	7	10	0.76	2.61	0.96	6.79	1.00	1.04	0.13	0.47	1.14	1.18	0.27	0.52	2.04	2.97	0.97
	7	47	0.73	2.42	0.35	0.75	2.28	1.32	-0.60	0.97	7.20	8.06	-4.27	4.22	3.60	7.82	0.99
	7	252	0.73	2.41	0.47	1.06	-0.88	-0.61	0.51	-1.11	-1.10	-1.37	1.79	-2.35	-1.48	-1.22	0.90
	7	162	0.73	2.40	0.50	1.15	0.33	0.19	0.32	-0.52	0.31	0.32	0.72	-0.67	0.53	0.33	0.89
	7	59	0.73	2.38	0.53	1.26	-0.14	-0.74	1.35	-0.76	-0.11	-0.86	2.25	-0.88	-0.88	-0.44	0.97
	7	196	0.71	2.27	0.48	1.09	1.52	0.71	-0.41	0.47	0.89	0.77	-0.57	0.38	2.23	0.88	0.57
	7	38	0.71	2.27	0.31	0.65	-13.06	-9.42	3.60	-2.98	-0.77	-0.79	0.82	-0.84	-22.47	-0.78	0.48
	7	17	0.71	2.22	0.37	0.81	0.54	0.91	0.53	0.09	0.82	1.05	0.72	0.05	1.45	1.22	0.87
	7	15	0.67	2.03	0.22	0.40	-0.74	-0.05	2.31	-3.50							
	7	100	0.61	1.73	-0.14	-0.27	-0.53	-0.77	2.84	-3.35	-0.91	-0.63	1.41	-1.40	-1.29	-0.77	0.90
	7	34	0.61	1.73	-0.05	-0.09	2.16	1.40	-1.80	0.84	3.65	4.04	-7.06	1.98	3.56	3.92	0.99

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Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years	Total	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		
	of Data	Emp-Years	Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
[redacted]	7	12	0.60	1.69	0.69	1.90	1.46	4.18	-1.01	-6.31	1.14	1.33	-0.55	-2.46	5.64	1.53	0.99
	7	16	0.60	1.67	0.68	1.85	0.81	0.54	0.75	0.35	0.11	0.15	0.24	0.07	1.35	0.14	0.82
	7	224	0.59	1.64	0.33	0.70	1.58	0.63	-0.86	0.91	1.44	1.03	-2.22	1.42	2.21	1.32	0.87
	7	27	0.59	1.62	-0.59	-1.47	-2.44	0.08	0.44	-1.28	-0.37	0.02	0.24	-0.25	-2.36	-0.24	0.75
	7	52	0.58	1.59	-0.79	-2.62	-0.26	0.23	-0.06	-0.07	-0.49	0.88	-0.33	-0.20	-0.03	-0.04	0.92
	7	31	0.54	1.45	0.67	1.83	2.56	0.74	0.13	0.92	0.54	0.30	0.06	0.26	3.30	0.50	0.76
	7	878	0.50	1.31	0.59	1.48	1.85	0.75	-0.70	0.51	46.85	35.03	-45.73	19.62	2.60	43.87	1.00
	7	88	0.49	1.27	-0.79	-2.57	-0.24	0.32	-0.37	0.19	-2.49	6.95	-11.05	3.14	0.08	0.54	1.00
	7	9	0.49	1.26	0.61	1.34	-2.99	-4.04	3.39	-3.51							
	7	14	0.42	1.04	0.60	1.48	5.60	3.82	-2.25	1.36	2.90	2.25	-2.54	0.88	9.42	3.07	0.96
	7	15	0.39	0.95	0.62	1.59	7.30	2.86	-2.56	3.35	5.09	4.58	-3.84	3.05	10.16	5.44	0.97
	7	68	0.38	0.91	-0.51	-1.17	-4.24	-1.64	1.33	-1.91	-0.76	-0.62	0.88	-0.79	-5.88	-0.72	0.64
	7	34	0.36	0.85	-0.62	-1.57	-0.33	0.65	-0.02	0.24	-0.27	1.18	-0.05	0.27	0.32	0.19	0.93
	7	11	0.34	0.81	-0.14	-0.27	3.17	2.67	-1.80	1.00	0.34	0.63	-0.44	0.15	5.84	0.45	0.55
	7	12	0.31	0.74	0.60	1.29	-8.69	-11.14	12.08	-6.51							
	7	47	0.24	0.55	0.29	0.61	2.29	1.15	-0.73	0.52	0.66	0.61	-0.66	0.29	3.44	0.65	0.46
	7	24	0.12	0.26	0.09	0.17	4.06	2.08	-1.49	2.58	18.07	20.25	-14.21	15.65	6.14	19.43	1.00
	7	14	0.08	0.17	0.24	0.50	0.71	-0.45	0.92	0.81	0.43	-0.54	1.27	0.70	0.27	0.11	0.95
	7	187	-0.08	-0.17	0.37	0.78	-0.10	-0.08	0.12	-0.82	-0.08	-0.12	0.24	-0.97	-0.18	-0.10	0.77
	7	10	-0.18	-0.42	0.29	0.62	15.96	30.79	-17.07	35.69	5.13	4.95	-4.84	5.17	46.74	5.01	0.98
	7	15	-0.22	-0.50	0.53	1.26	1.02	-0.23	0.62	-0.63	0.20	-0.09	0.27	-0.16	0.79	0.10	0.56
	7	17	-0.43	-1.07	0.48	1.10	5.55	2.37	-2.37	1.63	3.35	2.98	-3.45	1.37	7.92	3.33	0.96
	6	201	0.97	7.68	0.90	3.51											
	6	98	0.96	7.13	0.97	6.67											
	6	8	0.96	6.83	0.92	4.03											
	6	222	0.95	5.98	0.92	4.09											
	6	8	0.95	5.93	0.72	1.48											
	6	28	0.93	5.17	0.09	0.15											
	6	72	0.92	4.79	0.48	0.95											
	6	17	0.92	4.72	0.83	2.13											
	6	25	0.91	4.36	0.24	0.35											
	6	131	0.91	4.26	0.91	3.08											
	6	12	0.90	4.06	0.78	1.78											
	6	18	0.90	4.03	0.86	2.35											
	6	402	0.89	3.99	0.79	2.26											
	6	41	0.89	3.96	0.90	2.05											
	6	77	0.89	3.95	0.77	2.12											
	6	12	0.88	3.76	0.76	1.68											
	6	36	0.88	3.74	-0.03	-0.05											
	6	8	0.87	3.57	0.13	0.22											
	6	93	0.87	3.55	0.56	1.16											
	6	23	0.87	3.50	0.91	3.87											
	6	31	0.85	3.28	0.68	1.61											
	6	53	0.84	3.09	-0.14	-0.25											
	6	485	0.84	3.07	0.76	2.02											
	6	12	0.84	3.06	0.62	1.37											
	6	44	0.83	3.00	0.56	1.17											
	6	7	0.83	2.96	0.68	1.62											
	6	21	0.82	2.89	0.38	0.59											
	6	15	0.82	2.89	0.70	1.39											
	6	6	0.78	2.52	0.68	1.32											
	6	8	0.78	2.48	0.97	5.92											
	6	22	0.77	2.45	0.61	1.34											
	6	14	0.75	2.25	0.43	0.84											
	6	20	0.75	2.24	1.00	19.25											
	6	18	0.73	2.16	-0.06	-0.10											

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Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years	Total	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		
	of Data	Emp-Years	Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
[redacted]	6	149	0.71	2.03	0.98	7.11											
	6	22	0.68	1.86	0.36	0.66											
	6	10	0.61	1.56	0.98	8.07											
	6	8	0.55	1.32	-0.12	-0.18											
	6	14	0.52	1.20	0.93	2.58											
	6	10	0.51	1.19	-0.65	-1.47											
	6	34	0.51	1.18	-0.76	-1.67											
	6	15	0.49	1.14	0.50	0.99											
	6	9	0.42	0.93	0.35	0.52											
	6	31	0.41	0.90	0.16	0.16											
	6	12	0.27	0.55	-0.80	-2.34											
	6	8	0.24	0.49	-0.33	-0.61											
	6	13	0.23	0.47	0.89	2.81											
	6	10	0.21	0.42	0.67	1.28											
	6	40	0.18	0.37	0.60	1.29											
	6	24	0.09	0.18	0.42	0.65											
	6	11	-0.02	-0.04	0.58	1.23											
	6	10	-0.41	-0.90	-0.20	-0.20											
	6	170	-0.74	-2.21	0.06	0.10											

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Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years	Total	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		
	of Data	Emp-Years	Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
[redacted]	11	2981	0.60	2.26	0.97	12.05	1.50	1.01	-0.26	-0.34	10.44	2.21	-1.05	-1.42	2.51	4.97	0.99
	11	597	0.59	2.18	0.95	8.57	1.13	1.33	-0.48	-0.04	8.97	3.99	-3.14	-0.29	2.46	5.57	0.98
	11	293	0.54	1.91	0.97	11.05	1.50	1.17	-0.49	-0.08	8.38	2.13	-1.64	-0.29	2.67	3.97	0.97
	11	150	0.40	1.29	0.76	3.31	2.01	1.70	-0.80	-0.27	4.41	1.72	-1.21	-0.33	3.71	2.77	0.87
	11	140	0.26	0.81	-0.05	-0.13	0.69	1.28	-0.43	1.77	1.41	2.27	-0.74	2.01	1.97	2.14	0.71
	10	170	0.78	3.55	0.98	10.93	1.08	-0.18	0.15	0.12	4.91	-0.37	0.47	0.23	0.89	1.50	0.97
	10	1571	0.55	1.85	0.79	3.16	1.34	1.01	-0.36	0.02	13.75	6.15	-3.76	0.14	2.35	11.01	0.99
	10	69	0.49	1.60	-0.30	-0.78	-0.19	0.68	-0.18	0.15	-0.28	1.47	-0.42	0.17	0.50	0.57	0.52
	10	194	0.40	1.25	0.76	2.86	1.39	1.36	-0.33	-0.44	1.89	0.78	-0.27	-0.43	2.75	1.12	0.94
	9	57	0.67	2.39	0.08	0.21	0.62	0.82	-0.05	0.38	0.53	0.91	-0.07	0.24	1.44	0.92	0.40
	9	1073	0.64	2.22	0.69	2.34	1.15	0.25	0.30	-0.41	3.94	0.68	1.77	-0.85	1.40	2.74	0.89
	9	94	0.59	1.94	0.57	1.56	1.10	0.36	0.01	1.56	2.52	0.28	0.01	2.86	1.47	1.11	0.90
	9	81	0.54	1.70	0.77	2.94	1.63	1.09	-0.15	0.23	4.23	1.86	-0.49	0.46	2.71	4.12	0.92
	9	758	0.53	1.67	0.68	2.05	0.34	-0.90	0.56	-0.09	0.33	-0.28	0.37	-0.02	-0.56	-0.14	0.51
	9	46	0.17	0.46	0.74	2.70	2.01	0.71	-0.11	-0.23	2.20	0.66	-0.16	-0.18	2.73	2.07	0.75
	9	486	-0.01	-0.02	0.46	1.28	1.34	1.60	-0.55	0.31	4.91	3.62	-2.13	0.90	2.94	4.97	0.94
	8	113	0.80	3.25	0.91	4.90	0.44	0.22	1.21	-2.04	1.78	0.33	2.25	-5.15	0.66	0.73	1.00
	8	24	0.68	2.25	0.72	2.32	1.52	2.13	-0.81	-0.39	0.39	0.24	-0.10	-0.06	3.65	0.29	0.83
	8	29	0.61	1.87	0.76	2.62	2.07	2.81	-1.72	0.60	1.19	0.79	-0.53	0.22	4.88	0.93	0.83
	8	114	0.46	1.25	0.81	3.08	1.40	1.62	-1.07	0.50	0.84	0.48	-0.34	0.17	3.01	0.61	0.74
	8	22	0.33	0.87	-0.04	-0.10	0.37	0.68	0.51	-1.04	0.95	0.84	0.41	-0.53	1.05	0.99	0.97
	8	177	0.33	0.85	0.94	5.94	2.15	2.42	-2.11	1.22	2.70	1.46	-1.39	0.96	4.57	1.88	0.95
	8	206	-0.63	-2.00	0.13	0.30	1.48	5.60	-4.14	2.16	1.84	1.56	-1.55	1.36	7.08	1.74	0.93
	7	48	0.82	3.26	0.65	1.73	2.10	0.32	-0.98	3.09	6.73	1.26	-4.45	4.93	2.42	8.37	0.99
	7	22	0.74	2.48	0.87	3.60	2.05	1.38	-0.10	0.31	1.40	1.17	-0.13	0.20	3.43	2.57	0.93
	7	7	0.72	2.33	0.86	3.41	3.15	0.40	0.59	-0.24	1.69	0.08	0.14	-0.08	3.54	0.77	0.95
	7	43	0.70	2.17	0.54	1.28	0.89	1.50	-0.51	-0.15	2.01	1.58	-1.42	-0.52	2.39	1.78	0.82
	7	354	0.65	1.93	0.79	2.61	1.31	2.39	-0.84	0.14	6.24	3.53	-3.28	0.44	3.70	5.12	0.98
	7	58	0.62	1.75	0.71	2.01	0.76	3.57	-1.38	2.21	0.73	1.19	-0.94	1.30	4.33	1.71	0.87
	7	110	0.31	0.72	-0.45	-1.01	-0.86	1.35	-0.69	2.45	-2.20	2.04	-1.87	3.56	0.49	0.54	0.99
	7	143	0.21	0.48	0.90	4.19	1.05	-0.28	0.30	-0.40	5.44	-0.61	1.27	-1.51	0.77	1.34	0.98
	7	26	0.04	0.10	-0.21	-0.43	1.11	1.49	-0.29	-2.38	0.35	0.28	-0.06	-0.55	2.60	0.31	0.83
	7	136	-0.10	-0.23	-0.09	-0.18	1.45	2.96	-1.25	-0.62	2.56	3.71	-3.39	-1.23	4.41	3.45	0.93
	7	16	-0.33	-0.78	0.12	0.25	-0.39	1.05	-1.03	0.99	-0.83	1.32	-2.01	2.15	0.66	0.61	0.96
	7	378	-0.55	-1.49	0.73	2.11	1.15	4.61	-3.16	-0.29	1.93	1.31	-1.27	-0.30	5.76	1.56	0.86
	7	25	-0.73	-2.36	0.14	0.28	-0.19	0.70	-0.18	-0.23	-0.04	0.23	-0.07	-0.03	0.52	0.08	0.62
	7	15	-0.83	-3.37	0.60	1.52	0.27	0.93	-0.52	2.08	0.62	1.93	-1.36	4.48	1.20	1.59	0.98
	6	16	0.95	6.25	0.98	8.84											
	6	180	0.93	5.09	0.93	4.44											
	6	17	0.93	4.88	0.98	8.53											
	6	120	0.92	4.71	0.71	1.74											
	6	26	0.90	4.15	0.92	4.10											
	6	14	0.89	3.88	0.96	6.19											
	6	145	0.86	3.33	0.62	1.36											
	6	90	0.84	3.14	0.57	1.20											
	6	377	0.84	3.05	0.92	4.14											
	6	167	0.84	3.04	0.96	5.81											
	6	268	0.83	3.02	0.98	9.39											
	6	203	0.81	2.81	0.42	0.81											
	6	31	0.81	2.77	0.91	3.70											
	6	10	0.80	2.65	0.33	0.61											
	6	53	0.78	2.46	0.83	2.55											
	6	118	0.75	2.28	0.85	2.83											
	6	146	0.75	2.27	0.88	3.28											
	6	39	0.74	2.22	0.93	4.32											

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Job Title	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years	Total	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		
	of Data	Emp-Years	Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
[redacted]	6	96	0.71	2.02	0.95	5.47											
	6	39	0.71	2.01	0.74	1.93											
	6	91	0.71	2.00	0.49	0.97											
	6	8	0.69	1.92	0.68	1.62											
	6	26	0.67	1.81	0.19	0.33											
	6	26	0.58	1.41	0.28	0.51											
	6	31	0.57	1.39	0.77	2.08											
	6	9	0.54	1.27	-0.38	-0.71											
	6	8	0.52	1.22	0.78	2.14											
	6	405	0.46	1.02	0.60	1.30											
	6	230	0.43	0.96	0.69	1.63											
	6	14	0.42	0.93	0.36	0.67											
	6	23	0.41	0.91	0.09	0.15											
	6	15	0.40	0.88	0.17	0.30											
	6	8	0.38	0.82	-0.03	-0.06											
	6	12	0.38	0.81	0.44	0.85											
	6	18	0.35	0.75	0.27	0.49											
	6	78	0.33	0.70	0.38	0.70											
	6	38	0.33	0.69	0.85	2.82											
	6	115	0.29	0.60	0.09	0.15											
	6	37	0.28	0.58	0.59	1.27											
	6	102	0.23	0.48	0.66	1.51											
	6	74	0.07	0.14	-0.05	-0.09											
	6	24	0.05	0.10	0.48	0.94											
	6	338	0.01	0.01	0.43	0.82											
	6	17	0.00	-0.01	-0.30	-0.55											
	6	6	-0.05	-0.09	-0.13	-0.23											
	6	16	-0.09	-0.17	-0.15	-0.26											
	6	54	-0.12	-0.25	-0.93	-4.33											
	6	98	-0.13	-0.27	0.81	2.40											
	6	179	-0.24	-0.50	0.34	0.63											
	6	23	-0.26	-0.54	0.09	0.16											
	6	19	-0.29	-0.61	0.07	0.13											
	6	35	-0.36	-0.78	0.83	2.61											
	6	18	-0.38	-0.83	0.22	0.40											
	6	15	-0.40	-0.87	0.53	1.08											
	6	16	-0.46	-1.02	0.80	2.29											
	6	10	-0.47	-1.06	0.69	1.36											
	6	38	-0.85	-3.22	-0.92	-3.98											

Exhibit 2
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	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
	Years	Total	Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		
Job Title	of Data	Emp-Years	Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
TECHNICAL_DIRECTOR	11	1872	0.94	8.31	0.89	5.65	0.55	0.31	0.03	-0.02	3.08	0.63	0.60	-0.06	0.86	1.32	0.82
ARTIST_SKETCH	11	141	0.91	6.64	0.82	4.06	1.29	1.53	-0.12	0.18	7.17	4.44	-1.77	0.40	2.82	6.78	0.94
ENGINEER_SOFTWARE	11	503	0.91	6.41	0.93	7.25	0.95	0.70	0.01	-0.25	6.38	1.64	0.14	-0.62	1.65	3.78	0.91
ANIMATOR_SUPERVISING	11	70	0.82	4.35	0.89	5.41	0.23	2.42	-0.22	2.26	0.18	1.94	-1.18	1.85	2.65	5.34	0.89
ANIMATOR	11	772	0.81	4.21	0.78	3.53	0.55	0.48	0.06	-0.82	5.27	1.97	1.47	-3.57	1.03	3.32	0.92
ANIMATOR_DIRECTING	11	44	0.77	3.57	0.89	5.59	-1.79	3.71	0.06	2.65	-1.16	2.92	0.44	2.22	1.92	3.94	0.92
LAYOUT_ARTIST	11	129	0.75	3.37	0.79	3.68	0.91	1.27	0.15	0.47	3.97	3.23	1.90	0.79	2.18	5.50	0.92
ENGINEER_SR_SOFTWARE	11	53	0.74	3.31	0.79	3.59	0.70	1.61	0.00	0.79	1.75	2.89	0.03	1.11	2.32	5.27	0.89
DESIGNER_PRODUCTION	11	62	0.73	3.20	0.86	4.86	-0.52	2.50	-0.22	3.16	-0.22	1.55	-0.97	1.44	1.98	2.14	0.83
ANIMATOR_FIX	11	73	0.72	3.10	0.75	3.21	0.53	1.60	-0.05	0.10	0.86	2.81	-0.33	0.10	2.12	4.47	0.83
ART_DIRECTOR	11	70	0.70	2.95	0.76	3.26	1.18	0.70	-0.04	1.55	4.33	1.74	-0.33	1.81	1.89	3.36	0.83
ENGINEER_QUALITY_ASSURANCE	11	54	0.58	2.16	0.82	4.06	0.72	1.11	0.24	-0.86	1.07	1.77	1.00	-0.75	1.83	3.79	0.80
SYSTEMS_ADMINISTRATOR_SR	11	91	0.56	2.04	0.81	3.97	1.07	0.56	0.12	0.70	5.49	2.03	1.65	1.48	1.63	4.81	0.90
ARTIST_STORY	11	247	0.55	1.98	0.46	1.48	1.27	1.09	0.01	0.41	2.96	2.26	0.07	0.43	2.36	2.98	0.70
MGR_DESKTOP_SYSTEMS	11	11	0.51	1.79	0.81	3.89	1.08	0.42	0.01	1.19	4.76	1.69	0.09	1.88	1.50	4.24	0.86
SYSTEMS_ADMINISTRATOR	11	133	0.50	1.75	0.29	0.86	0.74	1.15	0.06	-0.16	1.93	2.43	0.51	-0.20	1.89	2.50	0.62
SCIENTIST_SR	11	62	0.50	1.74	0.39	1.21	1.06	1.26	-0.09	0.07	2.05	2.72	-0.49	0.06	2.31	2.91	0.68
TECH_DIRECTOR_SUPERVISING	11	70	0.49	1.67	0.72	2.95	1.91	0.66	-0.15	3.54	4.54	1.97	-0.89	3.08	2.56	4.81	0.87
MGR_FINANCIAL_SYSTEMS	11	11	0.43	1.41	0.84	4.41	0.91	0.34	0.00	0.90	5.48	1.95	0.03	2.06	1.24	4.99	0.88
ENGINEERING_MANAGER	11	11	0.42	1.38	0.83	4.20	0.88	0.24	0.08	0.56	4.82	1.10	1.22	1.12	1.12	3.60	0.86
ENGINEER_ASSOCIATE	11	11	0.42	1.38	0.88	5.34	0.84	0.21	0.04	0.53	5.76	1.20	0.67	1.39	1.05	4.31	0.88
ARTIST_GRAPHIC	11	42	0.42	1.37	0.63	2.29	1.15	0.84	0.08	1.67	3.63	2.51	0.76	1.85	1.98	3.68	0.79
ADMINISTRATOR_TECH_DEPT	11	24	0.38	1.22	0.86	4.72	0.60	0.02	0.09	-0.13	4.06	0.10	1.73	-0.36	0.62	2.11	0.84
TECH_DIRECTOR_LEAD_CRTV_SVCS	11	11	0.34	1.09	0.84	4.35	0.95	0.24	0.06	0.73	4.89	1.21	0.87	1.37	1.19	4.01	0.86
DEVELOPER_RENDERMAN_PRODUCTS	11	11	0.21	0.63	0.79	3.66	1.01	0.25	0.03	1.20	4.52	1.44	0.42	2.01	1.25	4.30	0.85
TECH_DIRECTOR_CRTV_SVCS	11	44	0.19	0.59	0.26	0.75	0.57	0.92	0.18	-1.39	2.12	3.91	1.80	-1.63	1.49	3.88	0.85
SCULPTOR	11	22	0.17	0.52	0.41	1.29	0.84	0.35	0.07	1.70	4.85	2.20	1.10	4.11	1.19	4.57	0.92
ENGINEER_PRODUCTION_SUPPORT	11	35	0.12	0.36	0.12	0.35	0.77	0.92	0.01	-1.08	1.17	1.57	0.04	-0.60	1.69	1.58	0.39
PROJECT_MGR_STUDIO_TOOLS	10	35	0.50	1.62	0.71	2.65	1.47	0.68	0.03	-4.53	2.67	2.62	0.15	-2.08	2.15	3.58	0.85
MGR_SYSTEMS_OPERATIONS	10	10	0.41	1.28	0.74	2.66	1.03	0.40	-0.20	2.10	3.42	1.19	-0.93	1.93	1.44	2.70	0.81
ENGINEER_RENDERMAN_SUPPORT	10	15	0.28	0.83	0.68	2.45	1.10	0.49	0.02	-0.34	2.08	1.33	0.06	-0.13	1.59	2.68	0.67
VP_SOFTWARE_ENGINEERING	10	12	0.26	0.76	0.56	1.79	3.29	0.66	0.72	-9.33	2.20	1.19	1.18	-2.35	3.95	2.37	0.89
USER_INTERFACE_DESIGNER	10	20	0.14	0.40	0.66	2.35	0.65	0.35	0.02	0.43	1.94	1.17	0.19	0.35	0.99	2.17	0.61
DIR_RENDERMAN_PRODUCT_DEV	9	9	0.34	0.95	0.78	3.01	1.66	0.14	0.12	2.32	3.77	0.40	0.55	1.91	1.80	3.41	0.88
DESIGNER_ENVIRONMENTAL	9	15	0.17	0.45	-0.43	-1.07	1.85	1.06	0.30	-1.74	5.23	12.17	6.25	-4.55	2.92	7.02	0.99
ARTIST_AFTER_EFFECTS	8	25	0.58	1.73	0.73	2.36	-0.34	1.69	0.31	-2.68	-0.22	2.03	0.66	-1.00	1.35	1.15	0.85
TECHNICAL_WRITER	8	13	0.35	0.92	0.63	1.60	0.56	0.96	0.85	-6.04	11.18	17.44	10.07	-16.87	1.52	20.27	1.00
TECHNICAL_LEAD_RENDERING	8	8	0.34	0.89	0.81	3.05	1.03	0.02	0.22	2.32	6.00	0.08	2.32	3.35	1.05	3.89	0.97
ARTIST_STORY_DEVELOPMENT	8	20	0.27	0.70	-0.03	-0.06	-0.05	0.57	0.11	-1.05	-0.10	2.80	0.51	-0.29	0.52	0.90	0.86
ARCHITECT_SYSTEM	7	11	0.98	10.74	0.85	3.29	1.66	0.21	-0.06	2.78	0.99	0.19	-0.21	0.75	1.87	1.13	0.83
TECHNICAL_LEAD_BACKUP_GROUP	7	8	0.96	7.73	0.90	4.22	-0.83	4.13	-0.40	2.52	-0.40	1.31	-1.32	1.09	3.30	2.38	0.93
ART_DIRECTOR_SHADING	7	22	0.95	6.70	0.78	2.52	0.55	1.40	0.06	0.28	1.35	1.81	0.93	0.23	1.95	2.38	0.94
TECHNICAL_DIRECTOR_LEAD	7	115	0.92	5.28	0.79	2.25	1.04	1.77	-0.06	-0.58							
ENGINEER	7	7	0.85	3.60	0.76	2.31	1.18	0.74	0.09	-0.79	5.27	3.52	3.33	-1.49	1.92	5.57	0.98
DIR_STUDIO_TOOLS	7	7	0.82	3.21	0.96	7.09	2.09	0.29	0.07	5.04	0.89	0.21	0.16	0.96	2.38	1.63	0.97
MGR_MEDIA_SYSTEMS	7	9	0.78	2.79	0.86	3.41	2.94	0.52	0.05	-1.45	4.09	0.72	0.45	-0.50	3.45	4.23	0.97
ENGINEER_SR_MEDIA_SYSTEM	7	12	0.76	2.65	0.18	0.36	1.90	1.47	0.15	-1.79	7.78	8.33	11.24	-5.53	3.37	8.20	0.99
MGR_TOOLS_WORKFLOW	7	7	0.56	1.50	0.77	2.39	1.06	1.29	-0.21	-9.01	0.65	3.32	-0.40	-3.41	2.35	1.54	0.98
ENGINEER_MEDIA_SYSTEMS	7	16	0.43	1.07	0.26	0.54	-0.71	0.69	0.07	2.87	-0.61	0.72	0.31	0.72	-0.02	-0.02	0.80
MGR_QUALITY_ASSURANCE	7	7	0.25	0.57	0.61	1.53	1.05	0.53	0.16	-0.85	18.35	16.92	22.03	-6.19	1.58	21.97	1.00
ENGINEER_PIPELINE	7	16	0.06	0.14	0.70	1.96	2.22	0.86	0.07	-0.01	2.35	3.50	0.68	-0.01	3.09	3.38	0.97
ENGINEER_RECORDING	7	7	0.02	0.05	0.92	4.69	0.97	0.26	0.01	0.02	509.00	279.12	44.62	3.82	1.22	620.48	1.00
HR_APPLICATION_DEVELOPER	7	7	-0.03	-0.06	-0.06	-0.11	0.09	1.52	0.50	-0.48	0.03	0.99	0.65	-0.07	1.61	0.50	0.53
RENDER_PIPELINE_SPECIALIST	7	19	-0.14	-0.32	0.55	1.33	1.06	0.37	0.29	0.00	6.82	5.52	15.44	0.01	1.43	7.54	1.00

Exhibit 2
Pixar

	Section 1		Section 2				Section 3				Section 4				Section 5		Section 6
			Level Correlation		Change Correlation		Regression Coefficients				Regression T-Stats				Net Effect		
Job Title	Years of Data	Total Emp-Years	Coeff	T-Stat	Coeff	T-Stat	Contemp	Lagged	Revenue	SJ Emp	Contemp	Lagged	Revenue	SJ Emp	C + L	T-Stat	r2
ENGINEER_SOFTWARE_TECHSUPPORT	7	7	-0.86	-3.77	0.01	0.03	-0.51	0.02	-0.01	2.20	-0.63	0.07	-0.03	1.07	-0.49	-0.55	0.58
ENGINEER_IMAGE_MASTERING	6	8	0.92	4.74	0.54	1.13											
TECHNICAL_LEAD_TELECOM	6	6	0.92	4.65	0.75	1.97											
ENGINEER_SCREENING_ROOM	6	6	0.88	3.76	0.79	2.24											
MGR_IMAGE_MASTERING	6	6	0.88	3.69	0.78	2.18											
CGI_PAINTER	6	65	0.74	2.20	0.53	1.07											
DESIGNER_CAMERA	6	6	0.60	1.50	0.76	2.00											
ENGINEER_APPLICATIONS	6	6	0.52	1.22	0.57	0.98											
FINANCIAL_APPS_DEVELOPER	6	6	0.46	1.03	0.80	2.31											
MGR_SR_PROJECT_STUDIO_TOOLS	6	6	0.46	1.03	0.21	0.31											
LAYOUT_ARTIST_LEAD	6	6	0.42	0.93	0.27	0.49											
MEDIA_SYSTEMS_COORDINATOR	6	8	0.12	0.24	-0.35	-0.66											